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Three Essays on Pricing and Inequality in Pharmaceutical Market

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Abstract of the Dissertation

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My thesis examines the pharmaceutical market from three different angles. The first two chapters examine the optimal pricing strategies from the pharmaceutical companies' and insurance companies' point of view respectively. In the last chapter, I analyze the racial and ethnic disparities in the drug use. Each of these essays is summarized below.

The first study provides a model that demonstrates the interplay between quality and product differentiation in determining the optimal pricing strategy. Specifically, higher (lower) quality products will engage in price skimming (penetration) strategies in markets where products are sufficiently differentiated, but will choose a market penetration (skimming) strategy in markets that are less differentiated. I tested this model using a unique database that combines information on drug price and quality for antidepressant drugs during the years 1999-2002. The results indicate that higher quality antidepressants engage in a market penetration strategy, charging initially lower prices that rise over time.

The second study examines how pharmaceutical costs are shared among consumers and insurers and how drug quality affects these costs. I provide a model which delineates the tradeoff between paying more for higher quality drugs to reduce future medical costs in determining the optimal copayment strategy for the third party payers. I test the model using two large drug therapeutic classes: brand name antidepressants and non-steroidal anti inflammatory drugs (NSAIDs). These two drug classes are interesting to study because they differ in the degree of variation in product quality. While there is little quality differentiation among the antidepressants studied, quality varies by more among the NSAIDS; hence, quality differences are more readily discernible. The results

indicate that consumers' out-of-pocket payments are larger for high quality antidepressants, while insurers pay less for these drugs. In contrast, insurers share the drug cost together with the consumers for higher quality NSAIDs.

In the third chapter, I seek to determine the extent to which disparities reflect differences in observable population characteristics versus heterogeneity across racial and ethnic groups in antidepressant drug use employing Blinder-Oaxaca decomposition technique. Using Medical Expenditure Panel Survey (MEPS) data from 1996-2003, I estimate individual out-of-pocket payments, total prescription drug expenditures, drug utilization, the probability of taking generic versus brand name antidepressants, and the share of drugs that are older, lower quality types of antidepressants (e.g., TCAs and MAOIs) for Caucasian, African American, and Hispanic individuals.

I find that substantive racial and ethnic disparities exist in all dimensions of antidepressant drug use examined. Observable population characteristics account for most of the differences in drug expenditures, with health insurance and education key factors driving differences in spending. Observable characteristics are also important in explaining racial and ethnic disparities in the probability of purchasing generics and in the quality of antidepressant drugs used. In contrast, differences in total utilization are not well-explained by observable characteristics, and may reflect unobserved differences in knowledge and cultural factors, which tells us that to limit differences in overall antidepressant drug use, policymakers must take into account unobserved heterogeneities, such as discrimination, knowledge, cultural background, etc. Thus, differences in observable characteristics (notably health insurance and education) explain racial and ethnic disparities in expenditures and patterns of use (e.g., brand vs. generic), but not disparities in total utilization.

To my loving family

Table of Contents

List of Figures

List of Tables

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Introduction

Pharmaceuticals account for a significant share of total health care expenditures in the United States. In 2003, Americans spent $179.2 billion on prescription drugs, almost 4.5 times the $40.3 billion spent in 1990. Importantly, the rate of spending growth for prescription medications outpaced other areas of medical care from 1995 to 2003. During the period from 1995 to 2002, pharmaceutical manufacturing was the most profitable industry in the United States (Kaiser 2005).

The rapid increase in pharmaceutical spending has generated both interest and controversy over drug pricing. Yet, there is little theoretical work or empirical evidence on pharmaceutical entry-pricing strategies or on the time paths of the prices of new entrants versus incumbents. In my first chapter, I am going to explore the entry pricing strategies of pharmaceutical manufacturers.

This study provides a model that demonstrates the interplay between quality and product differentiation in determining the optimal pricing strategy. In particular, higher (lower) quality products will engage in price skimming (market penetration) strategies in markets where products are sufficiently differentiated, but will choose a market penetration (price skimming) strategy in markets that are less differentiated. The reason is that in less differentiated markets, price competition is more important than quality competition for gaining market share and higher-quality firms are better able to garner greater market share through price cuts.

I test this model using a unique database that combines information on drug price and quality for antidepressant drugs during the years 1999-2002. Based on quality perceptions by physicians, the antidepressant market is a relatively homogeneous drug class, which consisted largely of selective serotonin reuptake inhibitors (SSRIs). The results indicate that higher quality antidepressants engage in a market penetration strategy, charging initially lower prices that rise over time.

In recent years, pharmaceutical costs have risen at double digit rates and have outpaced other medical care services such as physician services and hospital care. In 2005, expenditures for prescription drugs were $200.6 billion, almost five times larger than the $40.3 billion spent in 1990 (Kaiser 2007). There are a number of mechanisms designed to control the rapid growth in pharmaceutical expenditures. Cost sharing is one such mechanism, by forcing consumers to shoulder some fixed (copay) or proportionate (coinsurance) payments for each drug prescription. The most popular method of cost sharing is the use of multiple-tiered copayments.

Most previous work has focused on the effects of cost sharing on pharmaceutical utilization. But there is little research on how copayments are determined, and how insurers and consumers share in the cost of pharmaceuticals. My second chapter seeks to bridge these gaps in the literature. To my knowledge, this is the first study to examine how pharmaceutical costs are shared among consumers and insurers. I also consider drug quality as one of the key factors affecting consumer and insurer payments.

Although cost sharing may control pharmaceutical costs by increasing consumers' price sensitivity, it has also been shown to have unintended effects in terms of increasing health care utilization, such as hospital admissions and emergency room visits (Tamblyn 2001, Winkelmann 2004, Gibson, McLaughlin et al. 2001 etc.). Given this tradeoff, how do third party payers decide on the copayment structure that balances the current pharmaceutical costs and future health care utilization when they are offering drugs with different quality levels? These are the issues I address.

This study provides a model which delineates the tradeoff between paying more for higher quality drugs to reduce future medical costs in determining the optimal copayment strategy for the third party payers. In particular, if insurers believe they can save on future medical cost by offering the drug at a lower copayment, they are more likely to do so to encourage consumers to take the drug. Otherwise, they will charge a higher copay to reduce their current pharmaceutical costs.

The model is tested using two large drug therapeutic classes: brand name antidepressants and non-steroidal anti inflammatory drugs (NSAIDs). These two drug classes are interesting to study because they differ in the degree of variation in product quality. While there is little quality differentiation among the antidepressants studied, quality varies by more among the NSAIDS; hence, quality differences are more readily discernible. The results indicate that consumers' out-of-pocket payments are larger for high quality antidepressants, while insurers pay less for these drugs. In contrast, for the higher quality NSAIDs, insurers share the drug cost together with the consumers. These findings suggest that insurers shift the drug costs associated with

higher quality onto consumers when there is little perceived quality variation among drug alternatives but share in the costs of higher quality drugs when there is greater perceived variation in drug quality.

In the third chapter, I seek to understand whether and to what extent differences in observed characteristics such as income, education, and health insurance, and unobservable heterogeneities account for racial and ethnic disparities in antidepressant drug use. Little is known regarding racial and ethnic disparities in utilization, spending, and types of drugs purchased in the antidepressant market. Identifying the extent and causes of such disparities is important because depression is a common and chronic disease, with patients frequently suffering recurrences or relapses (Thase 1990). Thus, patients who suffer from depression typically engage in ongoing use of antidepressant drugs. Gaskin et al. (2006) and Wang (2006) find evidence suggesting that unobserved heterogeneities may play an important role in explaining the disparity in drug utilization between different racial/ethnic groups. Yet, there is no established literature identifying factors that can explain these disparities and quantifying the effects of these factors on treatment patterns.

To help answer these questions, I use the Blinder-Oaxaca decomposition technique (Blinder 1973; Oaxaca 1973). This method has received only limited application in health services research generally, and in studying racial and ethnic disparities in health services use in particular. It is, however, quite useful in that it can not only distinguish how much observed vs. unobserved characteristics affect disparities, but can also determine the importance of individual factors in contributing to disparities.

Such information should prove quite valuable from a policy perspective. Particularly, in this chapter, I seek to determine the extent to which disparities reflect differences in observable population characteristics versus heterogeneity across racial and ethnic groups in antidepressant drug use, employing the Blinder-Oaxaca decomposition technique. Using the Medical Expenditure Panel Survey (MEPS) data from 1996-2003, I estimate individual out-of-pocket payments, total prescription drug expenditures, drug utilization, the probability of taking generic versus brand name antidepressants, and the share of drugs that are older, lower quality types of antidepressants (e.g., TCAs and MAOIs) for Caucasian, African American, and Hispanic individuals.

I find that substantive racial and ethnic disparities exist in all dimensions of antidepressant drug use examined. Observable population characteristics account for most of the differences in drug expenditures, with health insurance and education key factors driving differences in spending. Observable characteristics are also important in explaining racial and ethnic disparities in the probability of purchasing generics and in the quality of antidepressant drugs used. In contrast, differences in total utilization are not well-explained by observable characteristics, and may reflect unobserved heterogeneities. This finding suggests that, in order to mitigate differences in overall antidepressant drug use, policymakers must take into account these unobserved factors, such as discrimination, knowledge, cultural factors. Thus, differences in observable characteristics (notably health insurance and education) explain racial and ethnic disparities in expenditures and patterns of use (e.g., brand vs. generic), but not

disparities in total utilization.

To develop policies to reduce racial and ethnic disparities, it is important to know the relative importance of observed and unobserved parts and identify individual factors that are associated with the differences. Smedley et al (2003) reported that inconsistent treatment can increase overall health care expenditures. This topic is particularly timely now, as the proportion of minorities in the United States is growing substantially (US Bureau of the Census 2004). Understanding the extent and causes of these disparities can lead to more consistent, appropriate and effective policies aimed at their reduction.

Chapter One

Entry Pricing and Product Quality: The Case of Antidepressant Drugs

ABSTRACT

The rising prices of pharmaceuticals have generated considerable, and often acrimonious, debate. Yet, there is little theoretical work or empirical evidence on pharmaceutical entry-pricing strategies or on the time paths of the prices of new entrants versus incumbents. This study explores the entry pricing strategies of pharmaceutical manufacturers.

Previous theoretical models have considered a "price skimming" strategy, with drugs entering the market at a premier relative to incumbents or a "market penetration" strategy, pricing the drug at a discount in the hope of gaining market share. The selection of appropriate strategy depends upon the degree of product differentiation and/or the nature of repeat purchase arrangements. However, these investigations have not examined the implications of product quality for entry pricing and pricing dynamics.

The present study provides a model that demonstrates the interplay between quality and product differentiation in determining the optimal pricing strategy. In particular,

higher (lower) quality products will engage in price skimming (market penetration) strategies in markets where products are sufficiently differentiated, but will choose a market penetration (price skimming) strategy in markets that are less differentiated. The reason is that in less differentiated markets, price competition is more important than quality competition for gaining market share and higher-quality firms are better able to garner greater market share through price cuts.

I tested this model using a unique database that combines information on drug price and quality for antidepressant drugs during the years 1999-2002. Based on quality perceptions by physicians, the antidepressant market I examine is a relatively homogeneous drug class, which consisted largely of selective serotonin reuptake inhibitors (SSRIs). The results indicate that higher quality antidepressants engage in a market penetration strategy, charging initially lower prices that rise over time.

JEL Classification: I110, L100, L110

1.1 INTRODUCTION

Pharmaceuticals account for a significant share of total health care expenditures in the United States. In 2003, Americans spent $179.2 billion on prescription drugs, almost 4.5 times the $40.3 billion spent in 1990. Importantly, the rate of spending growth for prescription medications outpaced other areas of medical care from 1995 to 2003. During the period from 1995 to 2002, pharmaceutical manufacturing was the most profitable industry in the United States (Kaiser 2005).

The rapid increase in pharmaceutical spending has generated both interest and controversy over drug pricing. Yet, there is little theoretical or empirical evidence on entry pricing strategies or the time paths of the prices of new entrants versus incumbents. This study explores the entry pricing strategies of pharmaceutical manufacturers. Previous work has suggested that market conditions determine whether entrants choose lower penetration prices or higher skimming prices. Specifically, in markets where products are relatively well-differentiated and repeat purchase arrangements are less common, entrants are thought to adopt a market-skimming entry pricing strategy, charging a relatively high initial price. However, in more homogeneous markets and in those where repeat purchases are more common, one might expect a market penetration pricing strategy by an entrant (Eaton and Lipsey 1989; Schmalensee 1982; Dolan and Jeuland 1981; Rao 1984). In such markets, there may be greater uncertainty as to whether the entrant's drug is a significant improvement. Thus, the manufacturer may adopt a low-price entry strategy to familiarize consumers with the product, reaping the benefits in the form of higher

market shares and prices over time.

Product quality has also been thought to affect entry pricing. For instance, Dean (1969) argued that higher-quality entrants will engage in a skimming strategy, while entrants that offer only marginal improvements will adopt a market penetration strategy, charging lower initial prices. Previous research seems to suggest that (1) the degree of product differentiation and nature of repeat purchase arrangements affect the decision to engage in skimming or penetration pricing strategies and (2) substantially higher-quality products tend to adopt skimming strategies while modestly better products will engage in market penetration strategies.

While earlier theoretical models considered the roles of product differentiation and repeat purchases on pricing strategies, existing models have not explicitly derived the role of quality in affecting entry pricing strategies and subsequent pricing decisions. Moreover, existing studies on the effects of product differentiation and repeat purchase arrangements on entry pricing are fundamentally *across- market* issues, i.e., they account for alternative entry pricing strategies across markets that are distinguished by their product differentiation and/or the nature of repeat purchases of their products. However, these studies do not tell us if and when firms within a product market might engage in skimming or market penetration pricing strategies. Implicitly, these models assume that all firms within a given market adopt the same entry pricing strategy.

Thus, no current theory suggests how firms *within a product market* choose to engage in skimming or market penetration pricing strategies based on differences in product

quality. Such a model would need to derive not only the relationship between quality and the entry price, but also the evolution of price over time.[1] Moreover, no previous work has examined the potentially important interactions between quality and product differentiation on optimal entry pricing strategies. In particular, no study has considered whether the relationship between product quality and pricing might vary depending upon the degree of product differentiation within a given market.

To help bridge these gaps in the literature, I provide a model in which entry pricing and pricing dynamics are determined as a function of product quality. Here, I demonstrate that the decision by manufacturers of higher-quality products to engage in skimming versus market penetration price strategies itself depends upon the degree of product differentiation within the market. In relatively homogeneous markets, market share is quite sensitive to price and a market penetration strategy is beneficial to makers of the higher-quality products. This is consistent with Comanor's (1986) assertion that price competition is more important when the market is relatively homogeneous.[2] In such cases, our model shows that market share *of the higher-*

[1] For example, to formally derive a skimming strategy, one needs to show conditions for which higher quality leads to a higher entry price and conditions under which that price declines over time.

[2] Comanor 1986: "…where sellers of new products have not been able to achieve substantial quality advantages, they rely more on price competition to enter a therapeutic market. Products that embody higher quality, on the other hand, are more distant from the competitive pressures of established products and can be priced at higher levels."

quality products is particularly sensitive to price, so that, for example, higher-quality drugs will set low initial prices to help generate greater market share. In more differentiated markets, firms manufacturing higher-quality products will optimally choose a market skimming strategy.

Our model is tested empirically using a nationally representative data set on drug utilization and expenditures combined with a physician survey on the quality attributes of drugs to examine the effect of drug quality on pharmaceutical pricing strategies. Our quality measure consists of a comprehensive physician assessment of drug attributes and it provides an overall index of a drug's efficacy and side effects.

Specifically, I examine the brand name antidepressant drug class during the period 1999 to 2002. Based on physician quality perceptions, the brand name antidepressant market is a rather homogeneous drug class, consisting largely of selective-serotonin reuptake inhibitors (SSRIs). Using the data described above, I find strong evidence that antidepressant drugs adopt a market penetration pricing strategy, that is, higher-quality antidepressants enter at lower prices, but their prices rise over time. Low-quality antidepressants enter at higher prices and their prices decrease over time. These results are consistent with our model, namely, that market share is particularly sensitive to price for antidepressants with relatively high quality. Thus, the optimal strategy for higher-quality antidepressants is to adopt a market penetration pricing strategy.

The remainder of this paper is divided into seven parts. Part II summarizes the literature on entry pricing and empirical work as it pertains to the pharmaceutical

industry. The antidepressant drug market examined in this study is described in Part III and the conceptual framework is presented in section IV. Part V describes the data and empirical models to be estimated and the results are presented in Part VI. Part VII summarizes the findings and their implications.

1.2. PREVIOUS WORK

There are two distinct types of rivals in pharmaceutical markets. First, there is competition from the branded substitutes, which typically embody different chemical entities and enjoy patent protection, and second, there is competition from generic versions of new and existing products (Rao 1984).[3] Unlike different generic versions of the same drug, brand name competitors are differentiated in terms of quality. As I am particularly interested in the role of quality in entry-pricing strategies, our analysis focuses on brand name-drugs.

1.2.1 THEORETICAL STUDIES

Dean (1969) distinguishes between two strategies for pricing new products:

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[3] In much of this literature, price competition is not considered until patents have expired and generic substitutes enter. For instance, Frank and Salkever (1997) find higher prices following generic entry, while Caves et al. (1991) find a slight decline in a branded drugs' price after the appearance of generic rivals. Grabowski & Vernon (1992) find the price trends of the original brand name drugs following generic entry differ by drug category. Thus, evidence on the effect of generic competition on the prices charged for the original brand name drugs is mixed.

"skimming" pricing and "penetration" pricing. Skimming is the strategy of setting a high introductory price and then lowering it over time, while penetration is the strategy of setting a low price for a new product to gain market share, raising the price thereafter. Dean suggests that skimming may be used to extract the highest willingness to pay among consumers. This strategy may also be adopted when a product has few "close rivals" in its early stages.[4] On the other hand, Dean asserts that penetration is more common when market share is very sensitive to the price or when the products face drastic (potential) competition. This work gives an insightful qualitative analysis, but does not provide a formal model.

A number of theoretical studies of pricing strategies followed Dean's seminal work. Schmalensee (1982) considers the riskiness of new products, suggesting that pioneering products should charge low entry prices, because the manufacturer must persuade customers to try its "ex ante risky product" in order to build its reputation. In addition, late entrants face substantial disadvantages relative to pioneering brands, so they need to set even lower introductory prices. Therefore, the optimal strategy for the later entrants is to differentiate themselves from the predecessor and avoid being perceived as a "me-too" brand.

Shapiro (1983) explored the optimal pricing strategy of a firm with an experience

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[4] That is, price skimming will occur in more differentiated markets. Dean discusses these ideas but does not formalize them in terms of a model. Eaton and Lipsey (1989) make a similar argument in the context of a spatial model of product differentiation.

product, in which consumers learn about quality through use of the product itself. He states that firms' pricing strategies may be categorized according to customers' initial evaluations of the product: overestimation and underestimation of the product (i.e. optimistic and pessimistic evaluations). If consumers overestimate the quality of the product, the firm will milk its reputation. In this case, the optimal strategy is to set a high introductory price and then decrease the price over time. In the underestimation case, the product's reputation must be established and the best strategy in this case is to set a low introductory price and raise it over time. Shapiro considered the role of consumers' information, but not product signaling from the supply side.

Bagwell and Riordan (1991) model entry prices as a signal of quality. At the beginning of the period, the firm sets a price and then consumers form their beliefs about product quality on the basis of this signal. This belief is updated each period. As consumers become more informed about the drug's quality, the price distortion lessens. The investigators argue that the most efficient way for the firm to signal high quality of new products is to charge high introductory prices.

The studies by Schmalensse (1982), Shapiro (1983) and Bagwell and Riordan (1991) shed light on how entry pricing may be affected by perceptions of quality (Schmalensee; Shapiro) and by the impact of price as a quality signal (Bagwell and Riordan). However, these studies do not explore the means by which products with different quality levels adopt different entry pricing strategies. Moreover, they do not consider the role of product differentiation on entry pricing.

Dolan and Jeuland (1982) devised the first study to explicitly model drug pricing

strategy in an intertemporal framework. They set up a theoretical model and interpret the skimming and penetration strategies according to the nature of demand. They conclude that market penetration pricing is optimal if repeated purchases of products are important and the skimming strategy is optimal if the demand is stable and production costs decrease over time. However, Dolan and Jeuland do not relate skimming or penetration strategies to variations in product quality.

1.2.2 EMPIRICAL STUDIES

Reekie (1978) investigated Dean's entry pricing ideas in the pharmaceutical market by examining the launching prices for 171 new molecular entities (NMEs) introduced into the U.S market between 1958 and 1975. He finds that the prices of new drugs with important therapeutic gains are significantly higher than the existing counterparts and that the prices of these drugs decline over time. In contrast, the prices of imitators are much lower than the existing drugs and these low initial prices are followed by increases in price over time.

Lu and Comanor (1998) explore the demand-side determinants for New Chemical Entity (NCE) prices. They examine the pricing strategies of 144 newly patented pharmaceuticals in the United States between 1978 and 1987, finding that the main explanatory elements are the "therapeutic value" of the product and the competition in the market. Their study shows that the introductory price of drugs representing "important therapeutic gains" can be two or three times those of existing products. However, the drugs that largely duplicated existing ones are typically priced at

comparable levels. They also examine the time path of drug prices following entry and find that the prices of the important new drugs declined by about 13% on average four years after entry into the market, while the prices of drugs with little or no therapeutic improvement rose by 22% on average.

Following Lu and Comanor's (1998) approach, Ekelund and Persson (2003) review the pricing strategies of 246 NCEs in the Swedish market and compare the results with those in the US market. The Swedish pharmaceutical market is highly regulated, with various forms of price-cap regulations and other regulatory initiatives to limit pharmaceutical costs. Using the methodology delineated in Lu and Comanor (1998), they also find that introductory prices are positively correlated with drug quality. In contrast to the results in the US market, however, they did not find evidence of market penetration pricing strategy. Instead, all prices decrease substantially over time.

Perhaps due to sample size considerations, empirical studies of entry pricing in the pharmaceutical industry only consider the effects of quality on pricing across drug product markets. In contrast, I explore the effects of quality on entry prices *within* a large drug product market – antidepressants. This approach allows us to examine whether and to what extent quality affects entry pricing within a specific drug product class and to examine whether drugs within the same product class adopt different entry pricing strategies. Before turning to our empirical tests, however, the following section describes the antidepressant drug product market.

1.3 THE MARKET FOR ANTIDEPRESSANT DRUGS

Depression is one of the most prevalent and debilitating disorders in the United States, having an estimated lifetime prevalence between 10 and 20 percent (Katon and Sullivan 1990; Kessler et al. 1993; 1994).[5] Depression is a chronic illness and patients frequently suffer recurrences or relapse (Thase 1990). As a result of the high prevalence and chronicity of depression, the market for antidepressant drugs is quite large. Recent evidence (Drug Benefits Trends 2005) indicates that 10 percent of women and 4 percent of men aged 18 and older currently take antidepressants. The report also shows that antidepressants were associated with the top 5 highest costs per member per year (PMPY) in 2002, averaging $50.46.

Antidepressant drug use is common and has increased substantially in recent years. According to results from the National Ambulatory Medical Care Survey comparing data from 1999 with similar data from 1985, antidepressant drugs accounted for 13% of the entire increase in pharmaceutical prescribing (Pomerntz 2003). Sales of antidepressants are quite substantial and are likely to remain so. Total revenues from sales of antidepressants in the U.S. are estimated to grow from $3.72 billion in 1996 to $14.34 billion by 2006 (Frost and Sullivan 2001 Figure 4-6). SSRIs have dominated these sales, accounting for nearly 90% of sales in 1996. (Frost and Sullivan 2001 Figure 4-7).

Antidepressant drugs are most commonly associated with the treatment of depression,

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[5] Given its high prevalence and chronic nature, the economic burden of depression is very large. Research indicates that the costs of depression totaled $83.1 billion in 2000 (Greenberg et al. 2003).

including major depression, dysthymia, and depression co-existent with anxiety disorders (Market Measures 2001, p. III-9). The oldest classes of antidepressant drugs include tricyclics (TCAs) and monoamine oxidase inhibitors (MAOIs), each of which have been available in the U.S. for decades. While these drugs are effective in the treatment of depression, they may have serious side effects. For instance, TCAs may be lethal when taken in overdose. As a result, these drugs are much less commonly used today. SSRIs began to appear in the late 1980s and 1990s. They have similar effectiveness to TCAs and MAOIs, but with better-tolerated side effects. Most recently, additional antidepressants have become available, including non-selective serotonin reuptake inhibitors (NSRIs) and selective norepinephrine reuptake inhibitors. Antidepressants thus include a number of brand name drugs which are only available by prescription. I studied nine drugs constituting the vast majority of brand-name antidepressant drug sales in the United States. These drugs are in three therapeutically interchangeable categories of medications: selective serotonin reuptake inhibitors (SSRIs), which include Prozac (fluoxetine), Zoloft (sertraline), Paxil (paroxetine), and Celexa (citalopram); selective norepinephrine reuptake inhibitors (SNRIs), which include Effexor (venlafaxine) and Effexor XR; and "other," a category that includes Wellbutrin SR (bupropion), Serzone (nefazodone) and Remeron (mirtazapine).

The antidepressant drugs included in our study are listed in Table 1. The drug introduction dates are taken from the FDA Orange Book. I also list physician's average perceived quality for each drug from the Market Measures (2001) surveys.

[INSERT TABLE 1]

1.4 CONCEPTUAL MODEL

1.4.1 TWO-PERIOD MODEL

I present a two-period model of a profit-maximizing pharmaceutical manufacturer. The firm chooses its drug's initial entry price and the price in the subsequent period. As the marginal production cost of pills is very low, we may ignore these costs without loss of generality.[6]

The firm chooses prices for its drug in each time period in order to maximize profits:

(1)

$$\max_{P_0, P_1} P_0\, \rho(P_0, P_0^m, Q, Q^m, \xi) Y_0 + \frac{P_1}{1+r}(\alpha \times m(P_1, P_1^m, Q, Q^m, \xi)\rho(P_0, P_0^m, Q, Q^m, \xi) Y_0 + m(P_1, P_1^m, Q, Q^m, \xi) Y_1)$$

where

P_0 = the drug's entry price

P_1 = the drug price in period 1

P_0^m = the average price of all other drugs in the market at time 0.

P_1^m = the average price of all the other drugs existing in the market at time 1

[6] In the pharmaceutical industry, research and development costs are quite substantial (Dimasi et al. 2003). Such costs are incurred well in advance of product launch and may be regarded as sunk costs at the time that pricing decisions are made. One could include production costs of pills by simply regarding the prices as being net of these small unit production costs without any changes in the model or its conclusions.

Q = the quality of the drug

Q^m = the average quality of all other drugs in the market [7]

Y_0 = the number of potential new consumers of the drug in period 0

Y_1 = the number of potential new consumers of the drug in period 1

$\rho(P_0, Q, P_0^m, Q^m, \xi)$ = the fraction of potential new customers in period 0 who purchase the drug $0 \le \rho \le 1$

$m(P_1, P_1^m, Q, Q^m, \xi)$ = the fraction of potential customers in period 1 who purchase the drug $0 \le m \le 1$

ξ = parameter measuring the degree of market differentiation. $0 \le \xi \le 1$ [8].

r = positive rate of discount

α = parameter measuring the rate of repeat purchases $0 \le \alpha \le 1$ [9]

In period 0, the drug is sold to ρY_0 customers and there are mY_1 new customers who purchase the drug in period 1. In addition, some fraction of those customers who bought in period 0 continue to purchase the drug in period 1 and this fraction will be

[7] According to the physician perceptions, the quality of drug does not change significantly over time. In this model, I assume the drug's own quality and the market quality remain the same in two periods.

[8] A higher value for ξ indicates greater market differentiation.

[9] A market with a high level of repeated purchases has a high level of α, i.e. α is close to one, meaning that more customers from pervious period will appear again in the second period because of the long-term treatment.

greater if the drug is used for long-term treatment (i.e., it requires more repeat purchases); the expression $\alpha m \rho Y_0$ gives the number of these customers. I assume that $\partial\rho / \partial P_0 < 0$; $\partial\rho / \partial Q > 0$; and $\partial^2 \rho / \partial P_0 \partial Q < 0$. That is, a higher price reduces the fraction of potential consumers who will purchase the drug while higher quality increases this fraction. The expression $\partial^2 \rho / \partial P_0 \partial Q < 0$ indicates that a lower entry price leads to greater market share and that this effect is greater in absolute value (more negative) with increasing product quality.[10]

I also observe that the fraction of potential new customers ρ not only depends on the drug's own price P_0 and quality Q, but also on the market price P_0^m, market quality Q^m, and degree of market differentiation ξ. Thus, the pharmaceutical market I envision is a form of monopolistic competition, in which the firm has to take into account market price and quality conditions when setting its own price. For purposes of analytic tractability, I take P_0^m, Q^m and ξ as given.

I assume that $\partial\rho / \partial P^m > 0$; $\partial\rho / \partial Q^m < 0$; $\partial^2 \rho / \partial P_0 \partial P_0^m < 0$; $\partial^2 \rho / \partial P_0 \partial Q^m > 0$. In other words, a higher market price will increase the share of consumers purchasing the firm's drug, but this effect is smaller at higher levels of that drug's price. A lower market quality will increase the drug's demand, with this negative effect being less at higher levels of that drug's price.

I further assume that $\partial^2 \rho / \partial P_0 \partial \xi > 0$ and $\partial^2 \rho / \partial Q \partial \xi > 0$. Thus, if a market is more

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[10] This may be illustrated with an explicit example:

Let $\rho(P, Q) = Q^{.5}P^{-.5}$

Then $d^2\rho/dPdQ = -.25Q^{-.5}P^{-1.5} < 0$.

differentiated, demand increases less with decreased price and demand increases more with higher quality. I posit that there exists a critical value ξ^*, above which the market can be considered as relatively differentiated and below which the market is relatively homogeneous.[11]

Maximizing (1) with respect to P_0 and P_1 gives:

(2) $$\rho + P_0 \frac{\partial \rho}{\partial P_0} + \frac{\alpha m P_1}{1+r} \frac{\partial \rho}{\partial P_0} = 0$$

(3) $$\frac{\partial m}{\partial P_1} = -\frac{m}{P_1}$$

Substituting (3) into (2), and total differentiating (2) I obtain the following comparative statics results:

(4) $$\frac{dP_0}{dQ} = -\frac{\frac{\partial \rho}{\partial Q} + P_0 \frac{\partial^2 \rho}{\partial P_0 \partial Q} - \frac{\alpha P_1^2}{1+r} \frac{\partial^2 m}{\partial P_1 \partial Q} \frac{\partial \rho}{\partial P_0} - \frac{\alpha P_1^2}{1+r} \frac{\partial m}{\partial P_1} \frac{\partial^2 \rho}{\partial P_0 \partial Q}}{2\frac{\partial \rho}{\partial P_0} + P_0 \frac{\partial^2 \rho}{\partial P_0^{\,2}} + \frac{\alpha m P_1}{1+r} \frac{\partial^2 \rho}{\partial P_0^{\,2}}}$$

By the second-order conditions for a maximum, the denominator in (4) must be < 0.[12] Thus, the denominator for expression (4) is negative and the sign of $\mathrm{d}P_0/\mathrm{dQ}$ depends upon the sign of the numerator. We can see that only the first term of the numerator is

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[11] We similarly assume $\partial m / \partial P_1 < 0$; $\partial m / \partial P_1^m > 0$; $\partial m / \partial Q > 0$; $\partial m / \partial Q^m < 0$; $\partial^2 m / \partial P_1 \partial Q < 0$; $\partial^2 m / \partial P_1 \partial Q^m > 0$; $\partial^2 m / \partial P_1 \partial P_1^m < 0$; $\partial^2 m / \partial P_1 \partial \xi > 0$ and $\partial^2 m / \partial Q \partial \xi > 0$.

[12] The denominator is unambiguously negative if, as seems reasonable, $\partial^2 \rho / \partial P_0^2 < 0$. This assumption implies that $\rho(P_0, Q)$ is a concave function of P_0. In this case, when P_0 is low, a slight change in P_0 will not influence ρ significantly. At higher levels of P_0, however, the fraction of new consumers will fall dramatically with further increases in P_0.

positive. If the positive effect of $\partial\rho/\partial Q$ dominates, we will observe the skimming strategy, i.e. d P_0/dQ >0. Note, however, that the three remaining negative terms in the numerator each involve the expression $\partial\rho/\partial P_0$. This expression will become more (less) important the less (more) differentiated is the market. Thus we can further interpret the sign of dP_0/dQ using market differentiation theory.

(i) Suppose the market is relatively homogeneous: $\xi < \xi^*$

Given this assumption, the negative effect of $\partial\rho/\partial P_0$ is more likely to dominate the positive effect of $\partial\rho/\partial Q$.[13] Therefore, d P_0/dQ is more likely to be negative.[14]

In other words, in a homogeneous market, a high-quality drug is more likely to enter with a lower initial price *because the market share is more sensitive to price for high-quality drugs* (recall that $\partial^2\rho/\partial P_0\,\partial Q$ <0). Thus, higher-quality drugs will be particularly successful in achieving significant market share by choosing a lower entry price. In addition, if dP_0/dQ <0, then lower-quality drugs in the market will enter at a higher price. For these drugs, market share will not increase as much when prices are decreased and thus the products may enter the market at a higher price.

(ii) Suppose the market is relatively differentiated, $\xi > \xi^*$

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[13] $\partial\rho/\partial Q$ will be a relatively small positive number given the assumption $\partial^2\rho/\partial Q\partial\xi > 0$.

$\partial\rho/\partial P_0$ will be a very low negative number given the assumption $\partial^2\rho/\partial P_0\partial\xi > 0$.

Therefore, d P_0/dQ is more likely to be negative.

[14] We may observe that in a homogeneous market, $\partial m/\partial P_1$ is also a very low negative number, which confirms our conclusion. In addition, we assume that the third order across differentiations is small enough to be ignored. For example, $\partial^3\rho/\partial P_0\partial Q\partial\xi = 0$.

In this case, the positive effect of $\partial\rho/\partial Q$ is more likely to dominate the negative effect of $\partial\rho/\partial P_0$ and other terms. [15] Thus, dP_0/dQ is more likely to be positive.

In other words, if the market is sufficiently differentiated, a high-quality drug is more likely to enter with a higher initial price. Here, the increased quality must generate a large enough increase in the customer base in period 0 to offset the negative impact of higher prices associated with this customer base.

In addition, if repeat purchases are uncommon, we would expect α to be low and the discount rate, *r*, to be high. Lower α and higher *r* would decrease the negative terms in the numerator of expression (4), raising the likelihood that dP_0/dQ >0. In contrast, higher α and lower *r* will raise the likelihood that dP_0/dQ <0. These observations suggest that higher-quality drugs tend to charge lower entry prices in a homogeneous market and in a marketplace where repeat purchases are more common.

Thus, when markets are relatively homogenous, price competition is more important for gaining market share and higher-quality drugs enjoy a comparative advantage in gaining market share through lower entry prices.

How will these entry prices compare to P_0^m, the average price of drugs already on the market? For sufficiently high levels of quality, these lower entry prices will be below the prices of drugs already on the market. In this case, higher-quality drugs will enter

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[15] $\partial\rho/\partial Q$ will be a large positive number given the assumption $\partial^2\rho/\partial Q\partial\xi > 0$.

$\partial\rho/\partial P_0$ will be a slightly low negative number given the assumption $\partial^2\rho/\partial P_0\partial\xi > 0$.

Therefore, dP_0/dQ is more likely to be positive.

at a discount relative to the market. Whether these entry prices are, in fact, lower than the prices of existing drugs is an empirical issue which I will examine below. When products are more differentiated, price competition assumes less importance and the higher quality drugs enter with higher prices. At sufficiently high levels of quality, the higher entry prices will exceed the existing prices of competitor drugs already in the market. Again, however, this is an empirical issue.

The effect of market quality on entry price is given by:

$$(5)\quad \frac{dP_0}{dQ^m} = -\frac{\frac{\partial \rho}{\partial Q^m} + P_0 \frac{\partial^2 \rho}{\partial P_0 \partial Q^m} - \frac{\alpha P_1^2}{1+r}\frac{\partial^2 m}{\partial P_1 \partial Q^m}\frac{\partial \rho}{\partial P_0} - \frac{\alpha P_1^2}{1+r}\frac{\partial m}{\partial P_1}\frac{\partial^2 \rho}{\partial P_0 \partial Q^m}}{2\frac{\partial \rho}{\partial P_0} + P_0 \frac{\partial^2 \rho}{\partial P_0{}^2} + \frac{\alpha m P_1}{1+r}\frac{\partial^2 \rho}{\partial P_0{}^2}}$$

As in expression (4), the denominator for expression (5) is negative and the sign of dP_0 / dQ^m depends upon the sign of the numerator. Only the first term of the numerator is negative. In other words, if the market quality has direct strong effect on the drug's own demand, we are more likely to observe dP_0 / dQ^m <0. Finally, the effect of market price on the firm's entry price is:

$$(6)\quad \frac{dP_0}{dP_0^m} = -\frac{\frac{\partial \rho}{\partial P_0^m} + P_0 \frac{\partial^2 \rho}{\partial P_0 \partial P_0^m} - \frac{\alpha P_1^2}{1+r}\frac{\partial m}{\partial P_1}\frac{\partial^2 \rho}{\partial P_0 \partial P_0^m}}{2\frac{\partial \rho}{\partial P_0} + P_0 \frac{\partial^2 \rho}{\partial P_0{}^2} + \frac{\alpha m P_1}{1+r}\frac{\partial^2 \rho}{\partial P_0{}^2}}$$

The denominator for expression (6) is negative and the sign of dP_0 / dP_0^m depends upon the sign of the numerator. We can see that only the first term of the numerator is positive. As long as the price effect on demand $\partial m / \partial P_1$ dominates cross price effects $\partial \rho / \partial P_0^m$, we are more likely to observe dP_0 / dP_0^m <0, and vice versa.

1.4.2 PRICING DYNAMICS

We may also use this model to study pricing dynamics by comparing the entry and subsequent period prices of drugs. Again, using the first-order conditions given in equations (2) and (3) and rearranging terms, we may write:

(7) $\frac{P_0}{P_1} = \frac{\frac{\alpha m}{1+r}\varepsilon_0}{\varepsilon_1 - \varepsilon_0}$, where $\varepsilon_0 = \frac{d\rho}{dP_0}\frac{P_0}{\rho}$ and $\varepsilon_1 = \frac{dm}{dP_1}\frac{P_1}{m}$=-1 from (2)

Since $P_0 / P_1 > 0$, $\varepsilon_0 \in [-1,0]$.

Therefore, we have (8) $\frac{P_0}{P_1} > 1$, when $-1 < \varepsilon_0 < -\frac{1+r}{1+r+\alpha m}$

(9) $\frac{P_0}{P_1} < 1$, when $\varepsilon_0 > -\frac{1+r}{1+r+\alpha m}$

These conclusions are consistent with demand theory. Demand elasticity ε_0 is relatively inelastic (as in Equation (9)), at the lower part of the demand curve (consider for example the linear demand curve) where price is low and the demand is large. Therefore, P_0 is more likely to be less than P_1 in this inelastic range. The opposite is true when ε_0 is relatively elastic, as in Equation (8).[16]

We can rewrite equation (8) in the form: P_0 / P_1 >1, when $-1 < \varepsilon_0 < -1/(1+\alpha m/(1+r))$

If α is large, *r* is low, and *m* is large, then the possible range for ε_0 enlarges, which

[16] In the extreme case of α=0, ε_0 and ε_1 are both equal to -1 from the f.o.c, and P_0 and P_1 are indeterminate. In this case, if there are no repeat purchases, a firm will set prices independently in the two periods.

means that P_0 is more likely to be greater than P_1. Conversely, if α is low, r is high, and m is low, then the possible range for ε_0 shrinks and P_0 is less likely to be greater than P_1.

1.4.3 SUMMARY

As our comparative static analysis demonstrates, a higher quality product does not necessarily enter the market at a higher price because pricing also depends upon on market conditions and the nature of repeat-purchases. Specifically, in a relatively homogeneous market and/or with more repeated purchases, market share is more sensitive to price for the high-quality drug than it is for the lower-quality drug. Therefore, the best strategy to gain market share is to set a lower initial price for a high-quality drug to gain market share. In a more heterogeneous market, market share is not as sensitive to price. Therefore we may observe the opposite strategy for a high-quality drug, i.e. a skimming strategy. In other words, price competition is more important when the market is relatively homogeneous.

These observations suggest that skimming and market penetration strategies depend upon the market characteristics and the nature of repeat purchase arrangements. The classic price-skimming strategy discussed in the literature occurs when a high-quality drug enters the market at a higher price that is subsequently lowered. Although this certainly may occur in our model, it is also possible that a high-quality entrant will charge a lower initial price. And, as discussed earlier, prices may rise or fall over time. Earlier discussions have focused on two scenarios: classic skimming, in which the

entrant charges a higher price that declines over time, and market penetration, in which a lower entry price is selected and price rises over time. Our analysis delineates conditions under which four scenarios may occur. These cases are summarized in Table 2.

[INSERT TABLE 2]

1.5 DATA AND ESTIMATION

1.5.1 DATA

Our analysis is based on data from the 1999-2002 Medical Expenditure Panel Survey (MEPS) conducted by the Agency for Healthcare Research and Quality (AHRQ). The MEPS database consists of a number of files, two of which were employed in our study. The Consolidated File is a person-year level database, which provides detailed consumer information on health care utilization and expenditures as well as patients' demographics, socioeconomic characteristics, health, and health insurance status. The Prescribed Medicines File is an event-level file that includes information on the utilization and payments for each drug used by survey respondents.[17] I converted the

[17] Household respondents provided information on the names of all outpatient medications used by each household member and the names and locations of the pharmacies where medication was obtained. They were also asked for permission to request records from these pharmacies. Pharmacy providers were asked to provide the data necessary to assign a national drug code, which is specific for manufacturers, ingredients, strength, package size, quantity dispersed, total charge, and sources of payments. The AHRQ performed detailed matching,

Prescribed Medicines File to the person-year level and then merged it with the Consolidated File for this study.

Measures of physician-perceived quality indicators of drugs are provided by Market Measures Inc. (2001), a private medical survey research company. Their survey was conducted among a physician panel recruited from a random sample of those who treat patients with specific drug product classes. For example, information on the perceived quality of antidepressant drugs was obtained from a panel of psychiatrists, internists, and family practitioners who regularly treat patients suffering from depression and who are thus familiar with alternative antidepressant drugs. The quality evaluation is the physicians' perceptions of the performance of the drugs in actual clinical practice, rather than reports from clinical trials by the manufacturers. Physicians provided rating scores of 1 to 5 for various attributes of a particular drug, with higher scores representing better quality.

Using this information, I constructed composite quality measures. Physicians were queried about 10 indicators of quality for antidepressants, including patient tolerability and the degree to which each drug had interactions with other drugs. Physicians rated each dimension of quality on a Likert scale from 5 (best) to 1 (worst) for all drugs in the class. Complete descriptions of these quality indicators are provided in Appendix 1. I computed the means of these valuations for each drug as the aggregate of the *QUALITY* measure. Therefore, our quality measure consists of

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imputation, consistency checks, sensitivity checks, and reconciliation algorithms.

the average score of physician perceptions of drug quality.[18]

The subjects I include in this study are persons who are 18 years and older who had health insurance during the survey year.[19] These criteria left a sample of 5,742 subjects for analysis.

1.5.2 ESTIMATION

I estimate price equations for antidepressant drugs of the form:

(10) $$\ln(P) = \alpha_0 + \alpha_1 X + \alpha_2 Q + \alpha_3 MktYear + \alpha_4 Q \times MktYear + \varepsilon$$

where P is defined as the average transaction price, i.e., the summation of patient payment and the insurer payment per prescription of a particular drug for each patient. Previous work on pharmaceutical pricing has typically used either wholesale prices or invoice prices, neither of which takes into account the substantial rebates and price discounts often obtained by third-party payers. (Congressional Budget Office, 1998). Our measure of the transaction price, however, is the true price received by the manufacturers after such rebates and discounts. All prices are inflation-adjusted to 2000 dollars using the medical care component of the consumer price index.

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[18] For the antidepressant data, some indicators are not requested every year. To get a large-enough sample size, we include the indicators that were generated from 1999 to 2002.

[19] We elected to exclude uninsured subjects because some of them may receive free drug samples, in which case our price measures could be biased. In fact, however, including this group produced results (available from the authors on request) that were quite similar to those in the text.

The variable *MKTYEAR* indicates how long the drug has been on the market. It is defined as the difference between the survey year and the drug's approval year. This variable is also a proxy for the aggregate level of marketing efforts, such as detailing and direct to consumer advertising, which correlate with the length of time that a drug has been on the market.[20]

Our quality measure is the average of the physicians' perception of the quality of each drug, as discussed in the previous section.[21] I also include an interaction term between

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[20] Such marketing efforts tend to be concentrated in the initial years following a drug's introduction and typically decline substantially thereafter (Grossman and Shapiro 1984).

[21] We consider the quality measure to be an exogenous variable in our model specification. One might argue that higher-priced drugs signal higher quality, so that the physician's perceived quality is to some extent a function of the drug's price. However, the evidence repeatedly demonstrates that physicians have very poor information about drug prices (Allan and Innes 2004; Conti et al. 1998; Glickman et al. 1994; Silcock et al. 1997; Walzak et al. 1994). If true, (1) actual prices should bear little relation to physician perceptions of prices and (2) physician's perceptions of price should bear little relationship to their perceptions of a drug's quality. Consistent with this evidence, our data indicate the physician's perception of a drug's cost is weakly correlated with the actual transaction price (rho = 0.08). Moreover, the correlation between physicians' awareness of an antidepressant drug's cost and their perception of the drug's quality is very low (rho = -0.02). In addition, our transaction price measure is at the individual patient level. Even if physicians did have some knowledge of the average wholesale price, they would have far less knowledge of individual transaction prices,

MKTYEAR and *QUALITY* to examine whether the relationship between quality and price varies with the length of time that the drug has been on the market.

The vector *X* includes other characteristics that could affect the transaction price, such as the health status, sociodemographic characteristics and drug insurance coverage of the patients/subjects. The names, descriptions, and summary statistics for variables used in this study are provided in Table 3.

To examine the effects of market quality (*MKTQUALITY*) and market price (*MKTPRICE*) on the drug price, I also estimated the following price equations: (11)

$$\ln(P) = \alpha_0 + \alpha_1 X + \alpha_2 Q + \alpha_3 MktYear + \alpha_4 Q \times MktYear + \alpha_5 MktQuality + \varepsilon$$
$$\ln(P) = \alpha_0 + \alpha_1 X + \alpha_2 Q + \alpha_3 MktYear + \alpha_4 Q \times MktYear + \alpha_5 MktQuality + \alpha_6 Mkt\,\mathrm{Pr}\,ice + \varepsilon$$

I controlled for heteroskedasticity in the above price regressions using the method proposed by Greene (1999) and Wooldridge (1999).[22]

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as our data confirm. Finally, because physicians do not bear the cost of the drug, they have less incentive to factor cost into their quality assessments.

[22] For example, we first obtain the predicted errors from (10), and then regress the square of the predicted error terms on all the independent variables in (10). The predicted fitted values are the weights we used to correct for heteroskedasticity. In a small percentage (1%) of cases the fitted values were negative and could not be used as weights. The results (reported in the text below) were quite similar whether or not we corrected for heteroskedasctivity.

[INSERT TABLE 3]

1.5.3 ANTIDEPRESSANTS REVISITED

Our theoretical model concludes that higher-quality drugs will enter with lower prices in markets that are not well differentiated and where repeat purchase arrangements are common. These features characterize the antidepressant drug market well. Thus, while Celexa and Wellbutrin SR have the highest quality ratings among the antidepressant drugs, their quality advantages are not substantially superior to other drugs in the group. Hence, it may be more difficult for consumers to perceive real differences in quality among the antidepressant drugs. In terms of our model, this suggests that we may be more likely to observe lower entry prices among high-quality drugs in the antidepressant marketplace.

The patterns on scrip use lend further support to these predictions. In particular, Table 1 indicates the average number of scrips filled per patient for antidepressants (4.70). When repeat purchases are important, our model predicts that higher-quality drugs will charge a lower entry price. Thus, we might expect to observe lower entry prices among higher-quality antidepressant drugs. The actual effects of quality on entry prices, as well as the time path of prices are empirical issues, however, to which I now turn.

1.6 RESULTS

1.6.1 QUALITY AND ENTRY PRICE

Table 4 provides the results of the multivariate price equations. Model 1 includes

interactions between the drug's quality and market year but does not correct for heteroskedasticity. Models 2-4 correct for heteroskedasticity. Model 3 adds market quality as an explanatory variable and model 4 adds market quality and market price.

Table 4 reveals that higher-quality antidepressants enter with lower initial prices, as the coefficient for *QUALITY* is negative and highly significant for antidepressants. The positive interaction between *QUALITY* and *MKTYEAR* indicates that, for antidepressants of sufficiently high quality, we will observe a market penetration strategy, with prices rising over time.

These patterns are consistent with both our model and our understanding of the antidepressant drug market. In choosing among brand-name antidepressants, a relatively homogeneous market, consumers may have greater difficulty determining whether new products constitute meaningful improvements. This factor, plus the greater degree of repeat purchases for antidepressants, suggest that charging a lower initial price may be a better long-run strategy for high quality entrants into this market.

Model 3 shows that market quality has a negative effect on the drug price, but the effect is not significant. Model 4 shows that market price has a significantly negative effect on the drug price. As indicated by Equation (6), the effect of market price on a drug's entry price is ambiguous. Entry price may be higher when the price of existing drugs is higher—a kind of positive spillover effect. On the other hand, a higher entry price may cause the firm to forego opportunities to gain market share from incumbent products by charging a lower entry price. Empirically, I find the latter effect dominates, so that the firm charges a lower entry price when the market price is higher.

Regardless of whether I control for market price and/or market quality in the model specification, I find the effect of drug quality on its price is always significantly negative and the magnitude of this effect changes little across specifications. Thus, the relationship between quality and entry price is robust.

We also note that the variable *HASRXINS* is negative and highly significant in the antidepressant regressions, implying that transaction prices for drugs are lower for persons who have drug benefits. In the literature, it has been argued (Congressional Budget Office, 1998) that drug manufacturers are more likely to offer discounts to institutions that have more control over drug distribution channels via entities such as drug formularies, a common feature of drug benefit plans. Our findings are consistent with the concept that plans offering drug benefits are able to obtain discounts, leading to lower transaction prices for the drugs purchased through these plans.

1.6.2 PREDICTED PRICES

Using the results from Model 2, I predict the entry price for each drug.[23] Specifically,

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[23] We use model 2 because we do not have market price and market quality for Prozac, which was the first drug in the SSRI class. We can obtain predicted values for the other drugs using models 3 or 4, which incorporate these market effects. These results are quite similar to those

I set the variable *MKTYEAR* to zero and estimate the real price of each drug when it entered the market. I also calculate the prices of the other drugs available at that time. I list these predicted prices in Table 5.

[INSERT TABLE 5]

Table 5 shows that the entry prices of Celexa and Wellbutrin SR, the two drugs with relatively higher quality, charged lower prices when they entered the market. Moreover, their prices were lower than the prices charged for drugs that were on the market when they entered. Thus, Celexa and Wellbutrin SR appear to have used the "market penetration" pricing strategy. In contrast, antidepressants associated with lower quality charged higher entry prices when they came into the market, consistent with the "price skimming" strategy.

Upon market entry, Celexa and Wellbutrin SR had a higher quality than the other available drugs, but the quality differentials were small in comparison to their competitors. As I hypothesized, when product differentiation is modest, higher-quality drugs charge lower initial prices, such as occurred with Celexa and Wellbutrin SR.

We can also use this model to compute the time paths for the prices of each drug. These are summarized in Figure 1.

[INSERT FIGURE 1]

Manufacturers of the higher-quality drugs -- Celexa and Wellbutrin SR -- charged lower initial prices and increased their prices over time, the so-called market

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reported in the text and are available from the authors on request.

penetration pricing strategy. According to our model, these higher-quality drugs entered the market at a lower price on the theory that they will be better able to gain market share. In contrast, Figure 1 reveals that lower-quality drugs such as Remeron and Serzone, entered the market with higher prices that then declined over time. Intuitively, when lower-quality drugs decrease their price, their gain in market share is less than occurs with higher-quality drugs. Thus, there is less incentive for the lower-quality drugs to be given a low initial price.

Figure 1 also reveals that at about five years post-entry, the prices of the drugs tend to converge, and then prices tend to diverge. This pattern is consistent with a consumer-search model. Recall that our quality measure is the physician's perception of the *average drug quality*. Consumers also observe average drug quality ex-ante, but ex-ante quality may differ from the consumer's experience ex-post. The reason is that the effects of a given drug on any individual are often highly idiosyncratic. In addition, a particular drug may not be selected because some consumers may have contraindications to that drug even though it offers relatively high average quality. Other consumers may prefer a drug of slightly less average quality because it is on the formulary of their drug benefit plan and thus costs them less. Nonetheless, one would expect that most (but not all) consumers would initially prefer the higher-quality drugs with lower entry prices. This situation means that most consumers (and their physician agents) initially purchase drugs according to their average quality ratings,

but thereafter will switch among the drugs to find the one that works best for them.[24] It is a process of experimentation for an individual consumer. The drug that works best for an individual is not necessarily the drug has the highest average quality rating. Nevertheless, one might expect that, over time, relatively fewer consumers from the higher quality drug group will switch to the lower quality group and relatively more consumers from the lower quality group will switch to the higher quality group. Therefore, the market share for the high-quality drug will rise over time, while that of the lower-quality drug will decline. And, through such a process, it would not be surprising to find that the prices of lower-quality drugs decline over time while those of the higher-quality drugs rise, precisely the pattern that we observe.

1.7 CONCLUSION

In this study, I hypothesize that a drug's entry price should depend on the *interaction* between the therapeutic quality of the new agent and the degree of product differentiation in the market. Our theoretical model predicts that in markets where products are relatively well-differentiated, higher-quality entrants will tend to adopt a market-skimming pricing strategy, charging a relatively high initial price. In more homogenous markets, we expect a high-quality entrant to observe a market penetration pricing strategy. Markets in which repeat purchase arrangements are

[24] Although most people treated pharmacologically for major depression and related diseases receive treatments over an extended period of time, switching among antidepressants is a common phenomenon. See Woods and Rizzo (1997) for further details.

common would reinforce these patterns.

Empirically, I examined brand-name antidepressant drugs during the period 1999 to 2002. On the basis of physician quality perceptions, product differentiation appeared to be fairly modest. Moreover, the antidepressant market is associated with substantial repeat purchases of the drugs. Consistent with our model, I find that higher-quality entrants engaged in a "market penetration" entry pricing strategy.

Our results thus indicate that drugs *within a given product market* may adopt quite different entry pricing strategies. The optimal pricing strategy depends upon the quality of the drug and the degree of product differentiation across drugs within that product market. I also find that price differences across drugs tend to diminish over time. This finding is consistent with the idea that consumers experiment with the drugs over time and search for the drug that works best. Although our empirical application focuses on the pharmaceutical industry, our theory may be applied to the study of entry pricing and pricing dynamics in other product markets as well.

Table 1.1: Antidepressants Summary Statistics

Drug Name	Observation	Initiated Year	Quality	# Average S crips
SSRI				
Celexa	730	1999, Dec. 22	3.73	4.89
Prozac	991	1987, Dec. 29	3.56	5.17
Zoloft	1327	1991, Dec 30	3.6	5.24
Paxil	1330	1992, Dec. 29	3.45	5.15
SNRI				
Effexor	92	1993, Dec 28.	3.47	3.80
Effexor XR	319	1997, Oct 20.	3.58	5.05
OTHER				
Remeron	200	1996, Jun 14	3.28	4.54
Serzone	175	1994, Dec 22	3.42	4.30
Wellbutrin SR	578	1996, Oct 4	3.69	4.13
			Average Quality: 3.53	Average Scr ips: 4.70
			Weighted Average Quality: 3.56	Weighted A verage Scri ps: 4.96
N=5742	Mean Market Year: 8.10			

Table 1.2: Alternative Market Pricing Strategies

Classic Skimming	Modified Skimming	Classic Market Penetration	Modified Market Penetration
$dP_0/dQ>0$ $P_0 > P_1$	$dP_0/dQ>0$ $P_0 < P_1$	$dP_0/dQ<0$ $P_0 < P_1$	$dP_0/dQ<0$ $P_0 > P_1$
Quality competition dominates $-1 < \varepsilon_0 < -\frac{1+r}{1+r+\alpha m}$	Quality competition dominates $\varepsilon_0 > -\frac{1+r}{1+r+\alpha m}$	Price competition dominates $\varepsilon_0 > -\frac{1+r}{1+r+\alpha m}$	Price competition dominates $-1 < \varepsilon_0 < -\frac{}{1}$

Table 1.3: Antidepressants: Variable Names, Description, and Summary Statistics (includes all subjects aged 18 years or older who have health insurance) N=5742

Variable Names	Description	Mean	Std Dev
DEPENDENT VARIABLES			
AVGPAYTOT	Average total payment (summation of self and third party payment) for each drug during a calendar year	80.04	40.64
AGE, GENDER AND MARITAL STATUS			
AGE1834	DV=1 if subject's age is between 18 and 34 else = 0	0.17	0.38
AGE3549	DV=1 if subject's age is between 35 and 49 else = 0	0.37	0.48
AGE5064	DV=1 if subject's age is between 50and 64 else = 0	0.27	0.44
AGE6574	DV=1 if subject's age is between 65 and 74 else = 0	0.10	0.30
AGE75UP	DV=1 if subject's age is 75 and up else = 0	0.08	0.28
FEMALE	DV=1 if subject is female else = 0	0.74	0.44
RACE & ETHNIC			
WHITE	DV=1 if subject is white else = 0	0.54	0.50
BLACK	DV=1 if subject is black else = 0	0.05	0.21
HISPANIC	DV=1 if subject is Hispanic else = 0	0.10	0.30
OTHER	DV=1 if subject's ethnic is other else = 0	0.31	0.46
EDUCATION			
NOHS	DV=1 if subject has less than high school else = 0	0.09	0.28
SOMEHS	DV=1 if subject attended HS but did not graduate else = 0	0.16	0.36
HSGRAD	DV=1 if subject is HS graduate else = 0	0.31	0.46
SOMECOLL	DV=1 if subject attended college but did not graduate else = 0	0.16	0.37
COLLGRAD	DV=1 if subject is college graduate else = 0	0.21	0.41
GRADSCHL	DV=1 if subject attended graduate school else = 0	0.07	0.25
HEALTH STATUS			
HEALTHPOOR	DV=1 if subject's health is poor else = 0	0.14	0.34
HEALTHFAIR	DV=1 if subject's health is fair else = 0	0.20	0.40
HEALTHGOOD	DV=1 if subject's health is good else = 0	0.31	0.46
HEALTHVGOOD	DV=1 if subject's health is very good else = 0	0.26	0.44
HEALTHEXC	DV=1 if subject's health is excellent else = 0	0.10	0.30
LOCATION			
NORTHEAST	DV=1 if subject lives in North East Census Region else = 0	0.17	0.38
MIDWEST	DV=1 if subject lives in Midwest Census Region else = 0	0.24	0.43
SOUTH	DV=1 if subject lives in South Census Region else = 0	0.39	0.49
WEST	DV=1 if subject lives in West Region else = 0	0.20	0.40
YEAR			
YR1999	DV=1 if year is 1999 else = 0	0.18	0.38
YR2000	DV=1 if year is 2000 else = 0	0.19	0.39
YR2001	DV=1 if year is 2001 else = 0	0.30	0.46
YR2002	DV=1 if year is 2002 else = 0	0.33	0.47

Variable Names	Description	Mean	Std Dev
HEALTH INSURANCE			
HASRXINS	DV=1 if subject has Rx insurance during all or some of the period year else = 0	0.66	0.47
QUALITY INDEX			
QUALITY	Average of all the quality indicators	3.56	0.12
YEARS ON MARKET			
MKTYEAR	The Years the drug has been on the market	8.10	3.74

Table 1.4: Brand Name Drug Quality and Real Drug Prices with Dependent Variable : ln(Drug Price)

	Model 1		Model 2		Model 3		Model 4	
	Coef	P-Value	Coef	P-Value	Coef	P-Value	Coef	P-Value
QUALITY	-0.92	0.00	-0.83	0.00	-0.84	0.00	-0.70	0.00
MKTYEAR	-0.47	0.00	-0.43	0.00	-0.42	0.00	-0.40	0.00
*QUALITY*MKTYEAR*	0.13	0.00	0.12	0.00	0.12	0.00	0.11	0.00
MKTQUALITY					-0.16	0.68	-0.36	0.34
MKTPRICE							-6.14	0.00
AGE3549	0.05	0.03	-0.05	0.02	-0.05	0.02	-0.06	0.00
AGE5064	0.01	0.78	-0.09	0.00	-0.09	0.00	-0.11	0.00
AGE6574	-0.07	0.03	-0.13	0.00	-0.13	0.00	-0.14	0.00
AGE75UP	-0.04	0.20	-0.03	0.17	-0.03	0.17	-0.04	0.08
FEMALE	0.04	0.02	0.05	0.00	0.05	0.00	0.05	0.00
BLACK	-0.02	0.59	-0.04	0.24	-0.04	0.24	-0.04	0.16
HISPANIC	0.00	0.94	-0.13	0.00	-0.13	0.00	-0.13	0.00
OTHER	-0.02	0.23	-0.03	0.03	-0.04	0.04	-0.05	0.01
SOMEHS	-0.06	0.08	-0.09	0.00	-0.09	0.00	-0.08	0.00
HSGRAD	-0.05	0.10	-0.16	0.00	-0.16	0.00	-0.16	0.00
SOMECOLL	-0.02	0.49	-0.18	0.00	-0.18	0.00	-0.17	0.00
COLLGRAD	-0.03	0.40	-0.12	0.00	-0.12	0.00	-0.12	0.00
GRADSCHL	0.05	0.23	-0.04	0.31	-0.04	0.30	-0.03	0.50
HEALTHPOOR	-0.02	0.62	-0.01	0.65	-0.01	0.65	-0.01	0.71
HEALTHFAIR	-0.03	0.40	0.02	0.45	0.02	0.46	0.04	0.09
HEALTHGOOD	-0.04	0.20	-0.08	0.00	-0.08	0.00	-0.08	0.00
HEALTHVGOOD	-0.05	0.11	-0.10	0.00	-0.10	0.00	-0.09	0.00
HASRXINS	-0.06	0.00	-0.04	0.01	-0.04	0.01	-0.04	0.01
MIDWEST	-0.01	0.62	-0.02	0.26	-0.02	0.25	-0.04	0.09
SOUTH	-0.01	0.59	-0.12	0.00	-0.12	0.00	-0.13	0.00
WEST	-0.01	0.68	-0.06	0.02	-0.06	0.02	-0.07	0.01
_CONS	7.68	0.00	7.56	0.00	8.13	0.00	34.31	0.00
N	5742		5671		5671		5671	

ADJ. R SQUARE	0.02	0.14	0.14	0.16

Notes:

1. Drug price is adjusted by CPI Medical Care Component in 2000 dollars
2. All the people in the sample have some type of health insurances and are >=18 years of age.
3. Model 1: OLS estimation
4. Model 2: OLS estimation adjusted the heteroskedasticity. (Some predicted negative value cause 71 observations fewer.)
5. Model 3: OLS estimation with market quality, adjusted heteroskedasticity.
6. Model 4: OLS estimation with market quality and market price, adjusted heteroskedasticity.

Table 1.5: Predicted Entry Real Price of Antidepressants Compared to the Existing Drugs

Drug Name	Entry Year	Entry Price ($)	Quality	Existing Drugs	Weighted Average Price of Existing Drugs at Entry Year ($)**	Weighted Average Quality of Existing Drugs at Entry Year ($)**
Skimming Strategy						
Paxil	92.Dec	**92.74**	**3.45**		**82.41**	**3.54**
				Prozac	83.49*	
				Zoloft	81.59*	
Effexor	93. Dec	**90.90**	**3.47**		**85.61**	**3.53**
				Prozac	83.24*	
				Zoloft	81.76*	
				Paxil	91.26*	
Remeron	96. Jun	**106.67**	**3.28**		**84.75**	**3.53**
				Prozac	82.50*	
				Zoloft	82.25*	
				Paxil	86.99*	
				Effexor	87.16*	
				Serzone	90.90	
Serzone	94. Dec	**94.61**	**3.42**		**85.10**	**3.53**
				Prozac	82.99*	
				Zoloft	81.92*	
				Paxil	89.82*	
				Effexor	89.64*	
Penetration Strategy						
Celexa	99.Dec	**72.95**	**3.73**		**83.08**	**3.54**
				Prozac	82.00*	
				Zoloft	82.58*	
				Paxil	84.25*	
				Effexor	84.75*	
				Effexor XR	83.08*	
				Remeron	98.47*	
				Serzone	87.34*	
				Wellbutrin SR	77.93*	
Zoloft	91.Dec	**81.43**	**3.60**		**83.74**	**3.56**
				Prozac	83.74*	
Effexor XR	97. Oct	**83.08**	**3.58**		**83.66**	**3.54**
				Prozac	82.25*	
				Zoloft	82.41*	
				Paxil	85.61*	
				Effexor	85.95*	
				Remeron	102.49*	
				Serzone	89.10*	

				Wellbutrin SR	76.92*	
Wellbutrin SR	96. Oct	**75.93**	**3.69**		**85.35**	**3.52**
				Prozac	82.50*	
				Zoloft	82.25*	
				Paxil	86.99*	
				Effexor	87.16*	
				Remeron	106.67*	
				Serzone	90.90*	

** Weighted average drug prices are calculated using scrip shares as the weights.

* These are individual drug prices

Note:

1. The predicted estimates of antidepressants were obtained from the price equation adjusted for heteroskedasticity by number of scrips:

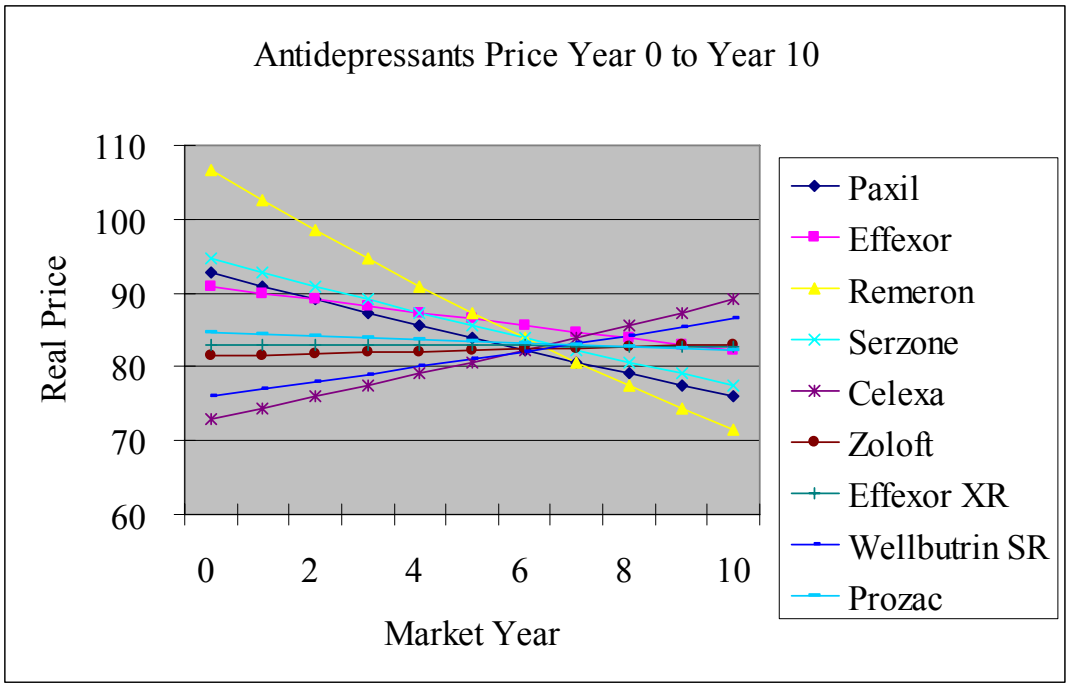
$$\ln \frac{P^t}{CPI^t} = \alpha_0 + \alpha_1 Q_t + \alpha_2 MktYear_t + \alpha_3 Q_t \times MktYear_t + \alpha_4 X + \varepsilon$$

We have:

$$\ln \hat{P} = -0.83 Q_t - 0.43 MktYear_t + 0.12 Q_t \times MktYear_t + \overline{X}\hat{\beta}$$

2. To transform $\ln \hat{P}$ to $\hat{P}$, we use the smearing estimate. The smearing factor in our study is 1.15.

Figure 1.1: Predicted Prices of Antidepressants for Each Drug from 0 to 10 Market Years



Appendix 1.1: Quality Indicators of Antidepressants

Variable	Description	Mean	Std. Dev.
QLTYLF	Improve Patient's Quality of Life	4.00	0.28
MLDMOD	Effective for Mild to Moderate Depression	4.08	0.25
ENERGY	Increased Energy Level/Activation	3.49	0.47
TOLERATE	Well-Tolerated by Patients	3.59	0.46
INTERAC	Few Interaction with Other Drugs	3.54	0.48
SEXUAL	Low Incidence of Sexual Dysfunction	2.86	0.49
CHGWEIGHT	No Weight Gain/Change	3.16	0.39
SEDATION	Low Incidence of Daytime Sedation	3.43	0.65
AGITATION	Minimal Agitation	3.50	0.25
RAPID	Rapid Onset of Action	2.95	0.17

Chapter Two:

Who Pays for Drug Quality?

ABSTRACT

Pharmaceutical costs have increased at double digit rates in recent years. Controlling further pharmaceutical cost increases seems urgent and cost sharing will play a critical role in such efforts. This study examines how pharmaceutical costs are shared among consumers and insurers and how drug quality affects these costs.

I provide a model which delineates the tradeoff between paying more for higher quality drugs to reduce future medical costs in determining the optimal copayment strategy for the third party payers. In particular, if insurers believe they can save on future medical cost by offering the drug at a lower copayment, they are more likely to do so to encourage consumers to take the drug. Otherwise, they will charge a higher copay to reduce their current pharmaceutical costs.

I test the model using two large drug therapeutic classes: brand name antidepressants and non-steroidal anti inflammatory drugs (NSAIDs). These two drug classes are

interesting to study because they differ in the degree of variation in product quality. While there is little quality differentiation among the antidepressants studied, quality varies by more among the NSAIDS; hence, quality differences are more readily discernible. The results indicate that consumers' out-of-pocket payments are larger for high quality antidepressants, while insurers pay less for these drugs. In contrast, for the higher quality NSAIDs, insurers share the drug cost together with the consumers. These findings suggest that insurers shift the drug costs associated with higher quality onto consumers when there is little perceived quality variation among drug alternatives but share in the costs of higher quality drugs when there is greater perceived variation in drug quality.

JEL Classification: I11; G22; L11

Key Words cost sharing; product differentiation; pharmaceuticals

2.1 INTRODUCTION

In recent years, pharmaceutical costs have risen at double digit rates and have outpaced other medical care services such as physician services and hospital care. In 2005, expenditures for prescription drugs were $200.6 billion, almost five times larger than the $40.3 billion spent in 1990 (Kaiser 2007). There are a number of mechanisms designed to control the rapid growth in pharmaceutical expenditures. Cost sharing is one such mechanism, by forcing consumers to shoulder some fixed (copay) or proportionate (coinsurance) payments for each drug prescription. The most popular method of cost sharing is the use of multiple-tiered copayments.[25]

Most previous work has focused on the effects of cost sharing on pharmaceutical utilization. But there is little research on how copayments are determined, and how insurers and consumers share in the cost of pharmaceuticals. The present study seeks to bridge these gaps in the literature. To our knowledge, this is the first study to examine how pharmaceutical costs are shared among consumers and insurers. I also consider drug quality as one of the key factors affecting consumer and insurer payments.

Although cost sharing may control pharmaceutical costs by increasing consumers' price sensitivity, it has also been shown to have unintended effects in terms of

[25] The most popular approach to cost sharing is the multiple-tier copayment structure. Usually the first tier includes the generic drugs and patients pay the lowest copayment. The second tier includes the "preferred" drugs by the health plan, and patients pay a higher copayment than for the first tier drugs. The third tier drugs include the "non- preferred" drugs, which have the highest copayments.

increasing health care utilization, such as hospital admissions and emergency room visits (Tamblyn 2001, Winkelmann 2004, Gibson, McLaughlin et al. 2001 etc.). Given this tradeoff, how do third party payers decide on the copayment structure that balances the current pharmaceutical costs and future health care utilization when they are offering drugs with different quality levels? These are the issues I address.

Specifically, I offer a theoretical model in which a third party payer controls the copayment level for a drug to minimize their costs. There are two parts to these costs: the current pharmaceutical costs and future medical care costs associated with taking or not taking the drug. The insurer is willing to pay more for the pharmaceutical cost provided doing so leads to sufficient medical care cost savings.

Insurers may be especially willing to pay more for drugs that are believed to confer substantive benefits. By taking such drugs, consumers may enjoy better outcomes and encounter fewer side effects, leading to lower future medical care costs. In this scenario, payers may incur higher initial pharmaceutical costs, but they will save on future medical care costs. On the other hand, if the insurer perceives that the therapeutic advantage of the drug over its competitors is minimal, they may not believe that they will enjoy future cost savings, leading them to charge a higher copayment for such drugs so as to minimize their current pharmaceutical costs.

With the advent of consumerism in health care, patients are being required to shoulder a larger share of costs generally (Lancet 2005; Robinson 2005). If such increases are imposed for costly services of little additional value, this may serve to promote

efficiency. But if cost increases are imposed without regard to quality differentials, inefficiencies and adverse health outcomes may result. Distinguishing between these two scenarios has considerable policy relevance (Lancet 2005). Our conceptual model and empirical analyses shed light on these issues.

I use a nationally representative data set on drug utilization and expenditures combined with a physician survey on the quality attributes of drugs to examine the effect of drug quality on third party pricing strategies and to test the hypotheses described above. Our quality measure is a comprehensive physician assessment of drug therapeutic attributes, and it provides an overall index of a drug's efficacy and side effects. I examine two therapeutic drug product markets: non-steroidal anti-inflammatory drugs (NSAIDs) and antidepressants during the period 1998 to 2002.

Based on physician quality perceptions, the NSAID product space has relatively greater quality differentiation than is the case for antidepressants. There are two drugs in particular among the NSAIDs -- Vioxx and Celebrex – that were widely perceived to offer substantively higher quality than competitor drugs at the time.[26] Third party payers could more readily perceive quality differentials among the NSAIDs and may thus be willing to pay more for higher quality NSAIDs. In contrast, the brand name antidepressants I study are relatively homogeneous. Third party payers may consider these drugs as having quite similar effects, and may not discern that higher quality antidepressants could lead to future cost savings.

[26] Subsequent to the period of our analysis, of course, these drugs were found to have serious adverse side effects.

Our results show that consumers' out-of-pocket payments are greater for high quality antidepressants, while insurers pay less for these drugs. On the other hand, insurers share in the higher drug costs of higher quality NSAIDs with consumers. These results are consistent with the view that insurers shift the drug cost associated with higher quality onto consumers when they believe that the quality differentials are trivial (hence may not lead to medical care cost savings), but share in these costs when they believe that quality differentials are more meaningful.

The remainder of this paper is divided into seven parts. Part II summarizes previous work, while the antidepressant and NSAID drug markets are described in Part III. The conceptual framework is presented in Part IV. Part V describes the data and models to be estimated, and the results are presented in Part VI. Part VII summarizes the findings and their policy implications.

2.2 PREVIOUS WORK

Due to the rapid growth in pharmaceutical expenditures, health insurers are seeking ways to control cost by managing utilization. Increased cost sharing, such as raising copayments, plays a critical role in controlling pharmaceutical costs. A number of previous studies have focused on the demand side and studied the effect of patient cost sharing on pharmaceutical utilization (Gaynor et al. (2006), Goldman et al. (2004), Landsman et al. (2001), Drug Benefit Trend (2004)), and consumer demand elasticity for pharmaceuticals ((Leibowitz (1985), Ellison et al (1997), Mortimer (1997)). In contrast, few studies have examined the determination of consumer's out-

of-pocket payments for prescribed medicines, and how this cost burden is shared with insurers.

On the supply side, prior research has investigated whether to adopt a particular drug onto a formulary. Evidence suggests that the adoption decision hinges upon a drug's efficacy, safety and cost (Shepherd and Salzman (1994), Mather et al. (1999), Sanchez (1996), Johnson and Friesen (1998) and Titlow et al. (2000)). For example, in a study of the decision making process of insurers, Titlow et al. (2000) find that "value judgment" plays an important role in the coverage decision. In particular, these insurers were asked to list the top five factors they considered when they made the coverage decision. Almost 75% of them mentioned the drug's "safety profile", followed by drug acquisition cost and availability of alternative treatments, with 46% and 44% respectively. Morgan (2002) suggests that both insurers and consumers will benefit from more studies to evaluate the cost effectiveness of competing drugs within a therapeutic class. However, there is no literature investigating how the insurer parses out payment for a drug between the consumer and insurer after it has been included on the formulary.

Although they did not examine drug quality effect directly, the above studies all mention that the therapeutic value of a drug is critical when the third parties make copayment decisions. It is worth noting in this regard that Lu and Comanor (1998) empirically model drug therapeutic value using the FDA therapeutic valuation for each approved drug as the quality measure. They find that therapeutic value is one of

the main factors affecting the average wholesale prices of New Chemical Entities (NCEs). That study focused on how drug quality affected the pricing decision of the pharmaceutical manufacturers. In contrast, I focus on how drug quality influences cost sharing among insurers and consumers.

2.3 THE MARKETS FOR NSAIDS AND ANTIDEPRESSANT DRUGS

The markets for NSAIDs and anti-depressant drugs in the United States are quite large. Recent evidence (Drug Benefit Trends, 2005) indicates that 10 percent of women and 4 percent of men aged 18 and older currently take antidepressants. Almost 27% of all visits to physician offices resulted in at least one prescription for an NSAID during the period 2001-2002 (Drug Benefit Trends, 2005). The report also shows that antidepressants and NSAIDs had among the top five highest costs per member per year (PMPY) in 2002, averaging $50.46 and $28.66, respectively.

I focus on cost sharing between insurers and consumers in this study. In this case, it is most relevant to examine patented brand name drugs because there are few strategic payment decisions for generic drugs by insurers. In most cases, when drugs lose patents, insurers charge the same level of copayments for all generic equivalents and market share for the branded drugs falls rapidly. Moreover, the two therapeutic classes I examine are dominated by patented brand name drugs. Thus, our analysis considers branded drugs only.

2.3.1 NONSTEROIDAL ANTI-INFLAMMATORY DRUGS (NSAIDS)

Non-Steroidal Anti-Inflammatory Drugs (NSAIDs) are known as Cyclooxygenase (COX) inhibitors. COX is an enzyme that is responsible for formation of important biological mediators called prostanoids. Pharmacological inhibition of COX can provide relief from the symptoms of inflammation and pain. NSAIDs inhibit the production of hormone-like substances that contribute to inflammation but also protect the stomach lining.

Damage to the gastrointestinal tract is the most serious potential adverse reaction to NSAIDs, though other potential adverse reactions occur as well (Medinfo, 2003). During the period of our analysis, the NSAID product market consisted of approximately a dozen brand-name prescription drugs. Celebrex and Vioxx were the two most recent entrants into this market, known as Cox-2 inhibitors. Our study focuses on brand–name NSAIDs that still enjoy patent protection—the vast majority of this market. Thus, I include: Celebrex (celecoxib), Vioxx (rofecoxib), Arthrotex (diclofenac and misoprostol), Daypro (oxaprozin) and Relafen (nabumetone). During the period of our study, these two drugs were thought to offer important therapeutic advantages by virtue of lowering the risk of gastrointestinal upset.[27]

Sales of NSAIDs are quite substantial, with total sales estimated at $9.4 billion in 2002 (Frost and Sullivan 2002). Celebrex and Vioxx were the leaders in NSAIDs sales, with combined sales of $4.4 billion during the period April 2002-March 2003 (Wellmark Report 2003). In terms of market share, as of 2000, Celebrex (41.8%) and

[27] Subsequently, of course, it was learned that these drugs increased cardiovascular risk, leading to the withdrawal of Vioxx from the market in 2004.

Vioxx (22.6%) were the leaders, followed by Relafen (8.6%), Daypro (4.9%), and Arthrotec (4.1%), with other NSAIDs accounting for smaller shares (IMS Health 2001).

2.3.2 ANTI-DEPRESSANT DRUGS

Depression is one of the most prevalent disorders in the United States. According to the report from National Institutes of Health, there are approximately 19 million adult Americans who suffer from clinical depression.[28] Depression is a chronic illness and patients frequently suffer recurrences or relapse (Thase 1990). Antidepressant drug use is common and has increased substantially in recent years. Antidepressant drugs are most commonly associated with the treatment of major depression, dysthymia, and depression co-existent with anxiety disorders (Market Measures 2001, p. III-9).

The oldest classes of antidepressant drugs include tricyclics (TCAs) and monoamine oxidase inhibitors (MAOIs), each of which have been available in the U.S. for decades. While these drugs are effective in the treatment of depression, they may have serious side effects and, for TCAs, may be lethal when taken in overdose. As a result, these drugs are much less commonly used today. Selective serotonin reuptake inhibitors (SSRIs) began to appear in the late 1980s and early 1990s. SSRIs drugs have similar effectiveness to TCAs and MAOIs, but with better-tolerated side effects. Most recently, additional antidepressants have become available, including non-selective serotonin reuptake inhibitors (SNRIs) and selective norepinephrine reuptake

[28] Given its high prevalence and chronicity, the economic burden of depression is very large. Research indicates that the costs of depression totaled $83.1 billion in 2000 (Greenberg et al. 2003).

inhibitors.

Currently SSRIs/SNRIs dominate the antidepressant market. Indeed, total sales of SSRI/SNRI antidepressants were $10.9 billion in 2003, making it one of the top three therapeutic classes (Drug Benefit Trends 2004). They are also the "second-most prescribed class of drugs" in the United States, according to IMS Health (Johnsen 2004).

I studied nine major drugs constituting the vast majority of brand name antidepressant drug sales in the United States. These drugs are in three therapeutically interchangeable categories of medications: selective serotonin reuptake inhibitors (SSRIs), which include Prozac (fluoxetine), Zoloft (setraline), Paxil (paroxetine), and Celexa (citalopram); serotonin noreponephrin reuptake inhibitors (SNRIs), which include Effexor (venlafaxine) and Effexor XR; and "other" category which includes Wellbutrin SR (bupropion), Serzone (nefazodone) and Remeron (mirtazapine).

The drugs included in our study are listed in Table 1. The drug introduction dates are taken from the FDA Orange Book. I also list physicians' average perceived quality for each drug from the Market Measures surveys.

2.4 CONCEPTUAL MODEL

In our framework, the third party payer controls the copayment level P_C and seeks to minimize its costs.

(1) Min

$$(P(Q,Q^M)-P_C)\times\alpha(P_C,Q,P_C^M,Q^M)\times N+\frac{1}{1+r}(\alpha\times N\times C^L+(1-\alpha)\times N\times C^H)$$

where

$P(Q,Q^M)$ = the drug's total price.

P_C = the drug's co-payment charged by the insurer.

$P-P_C$ = the price paid by the insurer

Q = the drug's quality

P_C^M = the average copayment of competitor drugs in the market

Q^M = the average quality of competitor drugs in the market

$\alpha(P_C,Q,P_C^M,Q^M)$ = the fraction of potential customers who purchase this drug $0\le\alpha\le 1$

N = the number of potential consumers who will buy the drug

C^L = expected medical costs incurred by the insurer when consumers purchase the drug

C^H = expected medical costs incurred by the insurer when consumers do not use the drug.

Insurers thus face two cost components: the drug cost for each prescription and other expected medical costs. I assume that other expected medical costs differ depending on whether or not consumers use the drug. If the drug is used, I assume that this

confers health benefits on the consumer such that other medical costs are lower than if consumers had not taken the drug; that is, $C^L < C^H$.

I specify total price P as a function of the drug's own quality Q and the average quality of competitors in the market Q^M. It is the lowest price that the insurer (or Pharmacy Benefit Manager PBM) could negotiate with the pharmaceutical manufacturer. I assume that $\frac{\partial P}{\partial Q} > 0, \frac{\partial P}{\partial Q^M} < 0$.[29] Higher drug quality leads to a higher P in equilibrium. That is the drug companies will be able to bargain for a higher equilibrium price P the higher the quality of their products and the lower the quality of competitor drugs in the market.

Given the negotiated total price P, insurers control the copayment level and thus determine how pharmaceutical costs are shared between themselves and consumers. According to this framework, αN consumers will purchase the drug. Thus, insurers incur $(P - P_C) \times \alpha \times N$ in total drug costs. I assume that medical costs incurred in the future are discounted at the level r. Such discounting of future costs (and cost savings) may reflect not only time preference, but also patient turnover rate. In particular, insurers may discount future cost savings more heavily if they believe that the turnover rate will be high.

I assume that $\frac{\partial \alpha}{\partial P_C} < 0, \frac{\partial \alpha}{\partial Q} > 0, \frac{\partial^2 \alpha}{\partial P_C \partial Q} < 0$. That is, a higher copay price reduces the

[29] This is a partial equilibrium model. In the first stage, insurers and pharmaceutical manufacturers negotiate a price P. Given this price, in the second stage insurers decide what copay to charge -- it is this second stage decision that we model. In some cases, pharmaceutical benefit managers (PBM) assist third party payers in negotiating the drug prices with the manufacturers. (Dranove et al. 2003) But they still need to act as agents for the insurers, taking into account the insurers' desire to limit their costs.

fraction of consumers who will purchase the drug while higher quality increases this fraction. The expression $\frac{\partial^2 \alpha}{\partial P_C \partial Q} < 0$ indicates that a lower copayment leads to greater consumer adoption rate, and this effect is greater in absolute value (more negative) the higher is a product's quality.

I also observe that α, the fraction of customers who purchase the drug, depends not only on the drug's price P_C and quality Q, but also on market copayment P_C^M and market quality Q^M. Thus, competitive pressures in the market affect demand for the drug as well. Consumers also consider the quality of the other drugs available when they decide to purchase the drug. I take P_C^M and Q^M as given.

I assume that $\frac{\partial \alpha}{\partial Q^M} < 0$ and $\frac{\partial^2 \alpha}{\partial P_C \partial Q^M} > 0$. That is, a lower market quality will increase the drug's demand and it will increase demand by less at a higher price. I also assume that $\frac{\partial \alpha}{\partial P_C^M} > 0$ and $\frac{\partial^2 \alpha}{\partial P_C \partial P_C^M} < 0$. That is, a higher market copayment will increase the drug's demand and it will increase demand by less at a higher price.

Minimizing (1) with respect to P_C gives:

$$-\alpha + (P - P_C + \frac{C^L - C^H}{1+r})\frac{\partial \alpha}{\partial P_C} = 0 \qquad (2)$$

We can see that $P - P_C + \frac{C^L - C^H}{1+r}$ must be negative to satisfy (2).

Totally differentiating Equation (2) and rearranging terms yields:

$$\frac{dP_C}{dQ} = \frac{\frac{\partial \alpha}{\partial Q} - \frac{\partial P}{\partial Q}\frac{\partial \alpha}{\partial P_C} - (P - P_C + \frac{C^L - C^H}{1+r})\frac{\partial^2 \alpha}{\partial P_C \partial Q}}{-2\frac{\partial \alpha}{\partial P_C} + (P - P_C + \frac{C^L - C^H}{1+r})\frac{\partial^2 \alpha}{\partial P_C{}^2}} \quad (3)$$

The denominator is positive by the second order condition. The first two terms of numerator are positive, and the third term is negative. Therefore the sign of $\frac{dP_C}{dQ}$ depends on the magnitude of these two parts. There are several cases to consider:

1. If the difference between C^L and C^H is sufficiently small, then $\frac{\partial P_C}{\partial Q}$ will be positive. That is, when insurers do not believe that higher quality drugs will translate into meaningful future cost savings for them, they will charge a higher copay and pay less themselves *for any given overall price P*.[30] On the other hand, if the insurer thinks that the drug will reduce other medical costs substantially, they will charge a lower copay (and pay more themselves) to encourage consumers to use the drug.
2. If $\frac{\partial \alpha}{\partial Q}$ is sufficiently large, $\frac{dP_C}{dQ}$ will be positive. Thus, if consumer demand is strongly responsive to higher quality, they will pay a higher copayment, and the insurer will pay less.
3. If $\frac{\partial P}{\partial Q}$ is sufficiently large, $\frac{dP_C}{dQ}$ will be positive. Thus, if the negotiated price increases sufficiently with higher quality, consumers will receive a higher copayment and the net cost to the insurer may rise or fall depending on the sign of

[30] Empirically, we may not observe that insurers pay less whenever the consumer pays more for drugs of different qualities. The reason is that these drugs may also have different overall prices *P*.

$$\frac{d(P(Q,Q^M)-P_C)}{dQ}.$$

4. If r is higher, $\frac{dP_C}{dQ}$ is more likely to be positive. If the insurer discounts medical cost savings from taking the drug more heavily, he will charge a higher copayment for the drug to save costs now.

2.4.1 OTHER COMPARATIVE STATIC RESULTS

The model also reveals how the optimal copayment depends upon other key parameters, including market copayment, quality and other medical costs. The effect of market quality on copayment is:

$$\frac{dP_C}{dQ^M}=\frac{\frac{\partial\alpha}{\partial Q^M}-\frac{\partial P}{\partial Q^M}\frac{\partial\alpha}{\partial P_C}-(P-P_C+\frac{C^L-C^H}{1+r})\frac{\partial^2\alpha}{\partial P_C\partial Q^M}}{-2\frac{\partial\alpha}{\partial P_C}+(P-P_C+\frac{C^L-C^H}{1+r})\frac{\partial^2\alpha}{\partial P_C^2}} \qquad (4)$$

The denominator of equation (4) is again positive by the second order condition. The sign of $\frac{dP_C}{dQ^M}$ thus depends on the sign of the numerator. The first two terms of the numerator are negative, while the third is positive. If higher market quality has a strong negative effect on consumer demand, we are more likely to observe $\frac{dP_C}{dQ^M}<0$.

The effect of the market copayment on P_c is given by:

$$\frac{dP_C}{dP_C^M}=\frac{\frac{\partial\alpha}{\partial P_C^M}-(P-P_C+\frac{C^L-C^H}{1+r})\frac{\partial^2\alpha}{\partial P_C\partial P_C^M}}{-2\frac{\partial\alpha}{\partial P_C}+(P-P_C+\frac{C^L-C^H}{1+r})\frac{\partial^2\alpha}{\partial P_C^2}} \qquad (5)$$

The denominator of equation (5) is again positive as before. The sign of $\frac{dP_C}{dP_C^M}$ thus

depends on the sign of the numerator. The first term of the numerator is positive, while the second is negative. If a higher market level of copayment has a strong positive effect on consumer demand, we are more likely to observe $\frac{dP_C}{dP_C^M} > 0$, i.e., we are more likely to observe that the insurer will increase the copay when others do.

2.4.2 SUMMARY

Our model asserts that third party payment for a drug is linked to perceptions of how taking the drug will affect future medical costs. If insurers believe that a drug offers meaningful quality improvements over existing drugs and will help them to save significantly on future medical care costs they are willing to pay more for these superior drugs. In other words, third parties are more likely to share the burden of the drug cost if they know that the drug can help them avoid or mitigate their future medical costs.

On the contrary, third parties will try to avoid the pharmaceutical cost burden if they do not believe that the drug will lead to significant savings in future medical costs. In this case, they place the burden of paying for higher quality on the shoulders of the consumers by charging them a higher copayment rate. We also observe that if consumers really care about higher quality (e.g., demand increases substantially for a higher quality drug), their copayment for that drug will be greater.

2.5 DATA AND ESTIMATION

2.5.1 DATA

I use the data from the 1998-2002 Medical Expenditure Panel Survey (MEPS) conducted by the Agency for Healthcare Research and Quality (AHRQ). I use two sub-files of MEPS for this study. The Consolidated File is a person-year level database and provides detailed individual information on health care utilization and expenditures as well as individuals' demographics, socioeconomic characteristics, health, and health insurance status. The Prescribed Medicines File is an event-level file that includes detailed information on the utilization and payments for each prescribed drug used by survey respondents.[31] I convert the Prescribed Medicines File to the person-year level and then merged it with the Consolidated File.

Physician-perceived quality indicators of drugs are provided by Market Measures Inc. (2001), a private medical survey research company. This survey was conducted among physicians who treat patients with specific drug product classes. For example, information on the perceived quality of anti-depressant drugs used a panel of psychiatrists, internists, and family practitioners who regularly treat patients suffering from depression and who are thus familiar with alternative anti-depressant drugs. The quality evaluation is the physicians' perception of the efficacy and side effects of the drugs in actual clinical practice. Physicians rated each dimension of quality on a

[31] Household respondents provided information on the names of all outpatient medications used by each household member and the names and locations of the pharmacies where medications were obtained. They were also asked for permission to request records from these pharmacies. Pharmacy providers were asked to provide the data necessary to assign a national drug code, which is specific for manufacturers, ingredients, strength, package size, quantity dispersed, total charge, and sources of payments. The AHRQ performed detailed matching, imputation, consistency checks, sensitivity checks, and reconciliation algorithms in assembling the Prescribed Medicines database.

Likert scale from 5 (best) to 1 (worst) for all drugs in the class.

Our sample includes subjects aged 18 to 64 who had any private health insurance during the survey year.[32] All of the individuals in our sample used one or more prescription drugs, and both third party payers and individuals incurred positive amounts of payments for drugs. These inclusion criteria left a sample of 906 and 2,618 subjects for NSAIDs and antidepressants, respectively.

2.5.2 ESTIMATION

I estimate price equations for antidepressant and NSAID drugs of the form:

$$Ln(SelfPay) = \alpha_0 + \alpha_1 Q + \alpha_2 MKTQLTY + \alpha_3 MKTCOPAY + \alpha_4 X + \varepsilon \quad (9)$$

$$Ln(ThirdPartyPay) = \alpha_0 + \alpha_1 Q + \alpha_2 MKTQLTY + \alpha_3 MKTCOPAY + \alpha_4 X + \varepsilon \quad (10)$$

The dependent variables are the natural log of the average individual and third party drug payment for a particular drug each year. I adjust these payments to constant dollars using the Medical Care component of the CPI, with 2000 as the base year. Our quality measure is the physician's perception of the average quality of each drug, as discussed in the previous section.

Using the Market Measures data described above, I construct composite quality

[32] We elected to exclude uninsured subjects because some of them may receive free drug samples, in which case our price measures could be biased. We also excluded those who have public health insurance. We believe that public insurers have different negotiation power with the drug manufacturers, e.g., OBRA 1990 regulates the "best price" for Medicaid enrollees. In fact, however, including these groups produced results (available from the authors on request) that were similar to those reported in the text.

measures. For each drug among the NSAIDs group, physicians were queried on eighteen indicators of drug quality, such as whether the drug is effective in pain relief or whether it is safe for extended use. Physicians were asked about ten indicators of quality for antidepressants. Descriptions of these quality indicators are provided in Appendix 1.

I computed the means of these valuations for each drug to construct our quality variables. This measure is reasonable, given that prior factor analysis of the individual quality indicators revealed that they were highly correlated. Thus, our summary measure is sufficient to capture overall quality while avoiding potential problems of multicollinearity.[33]

I also include the average quality of competitor drugs in the market (*MKTQLTY*) and the average copayment for these drugs *(MKTCOPAY)* to examine how these market-level variables affect individual and third party payment. Market quality is measured as the weighted average quality of competitor drugs, using scrip shares as the weights. The same procedure is used to calculate market copayments.

The vector *X* includes other characteristics that could affect transactions price, such as health status and socio demographic characteristics. The names, descriptions, and summary statistics for variables used in this study are provided in Table 2.

[INSERT TABLE 2]

[33] The result of this factor analysis is omitted in the interest of brevity but is available from the authors on request.

Before turning to our empirical results, it is worth examining some key differences between the NSAIDs and antidepressant drug markets. Table 1 shows the individual and weighted average qualities for each drug in the NSAID and antidepressant product markets. We can see that there are two NSAIDs in particular – Vioxx and Celebrex – which had markedly higher average quality ratings in comparison to their competitors. Hence, consumers and third parties may have been more readily able to perceive these quality differentials and view them as significant. In terms of our model, this suggests that third parties are more likely to share the cost burden with consumers for these drugs.

In contrast, while Celexa and Wellbutrin SR have the highest quality ratings among the antidepressant drugs, their quality advantages are substantially less marked than is the case for either Vioxx or Celebrex. Hence, insurers may be less likely to view these quality enhancements as leading to meaningful future cost savings. In terms of our model, this suggests that we may be more likely to observe that third party payers will shift some of the pharmaceutical cost burden onto consumers for antidepressants. The actual effects of quality on prices paid by the consumer and the third party are empirical issues, to which I now turn.

[INSERT TABLE 1]

2.6 RESULTS

2.6.1 NSAIDS

Table 3 shows the price equation estimates for the NSAIDs. The effects of drug quality are positive and significant for individual payment and for third party payment respectively. Thus, for the NSAIDs, consumers and insurers appear to be sharing in the cost of higher quality drugs.

Market quality has a positive and significant effect on individual payment. In terms of our comparative statics results (see equation 4), this suggests that market quality does not have a strong effect on the demand for an individual drug. Similarly, market copay has a negative and significant effect on individual payment, again suggesting that the market level copay does not have strong effect on consumer demand according to our theoretical model (see equation 5).

Females pay more for NSAIDs than males. Whites also pay more for the NSAIDs than do Hispanics and other racial groups. Third party payers pay more for the higher educated people, and these people pay significantly less for the drugs themselves. Third parties also pay more for people in poor health.

[INSERT TABLE 3]

2.6.2 ANTIDEPRESSANTS

Table 3 also shows the multivariate price equation results for the antidepressants. As the table indicates, drug quality has a significant positive effect on individual payment and a negative effect on third party payment that is approaching statistical significance. Thus, consumers must pay more for higher quality drugs while insurers

do not. For the antidepressant drugs we study, insurers appear to be shifting the cost of higher quality drugs onto the consumer.

Market quality has a positive and statistically significant association with individual payment. Market copay has a negative and statistically significant effect on the third party payment. Females pay more for their antidepressants. Whites also pay more for the antidepressants than do African American and Hispanics.

2.7 CONCLUSION

In this study, I hypothesized that the pharmaceutical cost shared by the insurer and the insured may differ by drug class. In particular, if quality differentials are small so that insurers do not believe that higher quality drugs will lead to significant cost savings for them, they are more likely to shift the higher drug cost onto the consumers. On the contrary, if quality differentials are more substantial so that insurers believe that higher quality drugs might lead to future cost savings, they are willing to share the higher pharmaceutical costs of these drugs with consumers.

Empirically, I examine brand-name antidepressant drugs and NSAIDs during the period 1998 to 2002. Based on physician quality perceptions, quality differentiation among the antidepressants is markedly less. Insurers may be less likely to believe that the modest advantages of higher quality drugs in this product class will lead to significant medical cost savings. Consistent with our model, I find that insurers shift drug costs to the individuals for the antidepressants. In contrast, they share the burden of the drug quality costs with the consumers for the NSAIDs where quality

differentials are greater.

In our static partial equilibrium model, third parties choose the copayment level to minimize their current pharmaceutical costs and future medical costs. An extension of our model may be generalized to a long-run decision making framework in which insurers consider not only drug costs but also their consumer base. An additional extension worth investigating would be to model the negotiation process between the insurer (or PBMs) and drug manufacturers. This would shed light on how overall prices are determined.

In recent years, consumer cost sharing has been rising in an effort to help contain growing pharmaceutical costs and health care costs generally. If cost sharing is increased judiciously in cases where the quality enhancements appear modest, this may serve to promote efficiency without sacrificing quality. However, if cost sharing rises across the board, quality may suffer. The present study provides at least some evidence that cost sharing may be implemented in a judicious fashion. In particular, I find that insurers share in the burden of costs in product markets when perceived quality differentials are substantial but not when they are quite modest.

Table 2.1A: Antidepressants Summary Statistics

Drug Name	Observation	Initiated Year	Quality
SSRI			
Celexa	367	1999, Dec. 22	3.73
Prozac	440	1987, Dec. 29	3.56
Zoloft	573	1991, Dec 30	3.60
Paxil	556	1992, Dec. 29	3.45
SNRI			
Effexor	33	1993, Dec 28.	3.48
Effexor XR	156	1997, Oct 20.	3.58
OTHER			
Remeron	60	1996, Jun 14	3.27
Serzone	88	1994, Dec 22	3.42
Wellbutrin SR	345	1996, Oct 4	3.69
			Average Quality: 3.53
N=2618			Weighted Average Quality: 3.58

Table 2.1B: NSAIDs Summary Statistics

Drug Name	Observation	Initiated Year	Quality
Celebrex	280	98 Dec 31	3.74
Vioxx	215	99 May	3.83
Arthrotec	66	97 Dec 24	3.31
Daypro	166	92 Oct 29	3.28
Relafen	179	91 Dec 24	3.35
			Average Quality: 3.50
N=906			Weighted Average Quality: 3.57

Table 2.2: NSAID & Antidepressants Variable Names, Description, and Summary Statistics (include all the people between 18 and 64 years older and have health insurance and private Rx insurance; and Self Pay>0; Private Insurer Pay>0)

		NSAIDs		Antidepressants	
		N=906		N=2618	
Variable Names	**Description**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
DEPENDENT VARAIBLES					
AVGPAYSLF	Individual's real average self payment for each drug during a calendar year (Base year 2000)	13.34	9.67	16.53	13.15
AVGPAYPRIVATE	The private health plan's real average payment for each drug during a calendar year (Base year 2000)	65.16	32.13	65.63	36.84
INDEPENDENT VARIABLES					
QUALITY INDEX					
QUALITY	Average of all the quality indicators	3.57	0.24	3.58	0.11
MKTQLTY	Weighted average quality of the other existing drugs	3.56	0.11	3.58	0.03
MKTCOPAY	Weighted average copay of the other existing drugs	13.54	1.90	16.52	1.10
AGE, GENDER AND MARITAL STATUS					
AGE1834	DV=1 if subject's age is between 18 and 34 else = 0	0.11	0.31	0.20	0.40
AGE3549	DV=1 if subject's age is between 35 and 49 else = 0	0.40	0.49	0.49	0.50
AGE5064	DV=1 if subject's age is between 50and 64 else = 0	0.49	0.50	0.31	0.46
FEMALE	DV=1 if subject is female else = 0	0.63	0.48	0.75	0.44
RACE & ETHNIC					
WHITE	DV=1 if subject is white else = 0	0.80	0.40	0.87	0.34
BLACK	DV=1 if subject is black else = 0	0.07	0.26	0.04	0.19
HISPANIC	DV=1 if subject is Hispanic else = 0	0.11	0.31	0.07	0.25
OTHER	DV=1 if subject's ethnic is other else = 0	0.02	0.12	0.02	0.14
EDUCATION					
NOHS	DV=1 if subject has less than high school else = 0	0.05	0.23	0.02	0.15
SOMEHS	DV=1 if subject attended HS but did not graduate else = 0	0.09	0.28	0.10	0.30
HSGRAD	DV=1 if subject is HS graduate else = 0	0.34	0.47	0.30	0.46
SOMECOLL	DV=1 if subject attended college but did not graduate else = 0	0.19	0.39	0.19	0.39
COLLGRAD	DV=1 if subject is college graduate else = 0	0.24	0.42	0.29	0.45
GRADSCHL	DV=1 if subject attended graduate school else = 0	0.09	0.29	0.09	0.29
ANNUAL INCOME					
INC50KUP	DV=1 if subject's income $50k and up else = 0	0.17	0.38	0.20	0.40
INC3050K	DV=1 if subject's income $30-$50k else = 0	0.27	0.44	0.27	0.44
INC2030K	DV=1 if subject's income $20k-$30k else = 0	0.22	0.42	0.17	0.38
INC1020K	DV=1 if subject's income $10k-$20k else = 0	0.16	0.36	0.16	0.37
INCLT10K	DV=1 if subject's income less than $10k	0.34	0.47	0.20	0.40

	else = 0				
HEALTH STATUS					
HEALTHPOOR	DV=1 if subject's health is poor else = 0	0.06	0.24	0.05	0.22
HEALTHFAIR	DV=1 if subject's health is fair else = 0	0.15	0.36	0.14	0.35
HEALTHGOOD	DV=1 if subject's health is good else = 0	0.35	0.48	0.33	0.47
HEALTHVGOOD	DV=1 if subject's health is very good else = 0	0.29	0.45	0.34	0.47
HEALTHEXC	DV=1 if subject's health is excellent else = 0	0.15	0.35	0.14	0.35
LOCATION					
NORTHEAST	DV=1 if subject lives in North East Census Region else = 0	0.18	0.39	0.16	0.36
MIDWEST	DV=1 if subject lives in Midwest Census Region else = 0	0.27	0.45	0.26	0.44
SOUTH	DV=1 if subject lives in South Census Region else = 0	0.43	0.49	0.39	0.49
WEST	DV=1 if subject lives in West Region else = 0	0.12	0.32	0.19	0.40

Table 2.3: NSAIDs & Antidepressants: Dependent Variable: Ln(Real Self Pay) and Ln(3rd Party PayPay)

	Nsaid				Antidepressant			
	Self Pay		3rd Party Pay		Self Pay		3rd Party Pay	
	Ceof	P	Ceof	P	Ceof	P	Ceof	P
QUALITY	0.49	0.00	0.79	0.00	0.41	0.00	-0.20	0.12
MKTQLTY	1.97	0.00	0.26	0.37	1.54	0.01	0.97	0.08
MKTCOPAY	-0.10	0.00	-0.05	0.00	-0.01	0.33	-0.03	0.01
AGE3549	0.00	0.98	-0.02	0.82	0.00	0.96	0.09	0.01
AGE5064	-0.02	0.79	0.05	0.58	0.01	0.89	0.00	0.98
FEMALE	0.10	0.03	-0.04	0.49	0.07	0.02	0.02	0.40
BLACK	0.05	0.58	-0.08	0.41	-0.18	0.01	0.02	0.77
HISPANIC	-0.24	0.00	0.05	0.52	-0.11	0.05	-0.03	0.52
OTHER	-0.31	0.08	-0.01	0.96	0.04	0.65	-0.06	0.46
SOMEHS	-0.25	0.04	0.06	0.64	-0.10	0.34	-0.06	0.54
HSGRAD	-0.18	0.11	0.11	0.36	-0.08	0.42	-0.03	0.73
SOMECOLL	-0.21	0.07	0.21	0.09	-0.01	0.90	-0.05	0.56
COLLGRAD	-0.19	0.09	0.09	0.46	-0.02	0.81	-0.02	0.84
GRADSCHL	-0.16	0.21	0.17	0.22	-0.05	0.67	0.07	0.44
HEALTHPOOR	-0.04	0.69	0.26	0.03	-0.02	0.82	0.01	0.86
HEALTHFAIR	-0.11	0.20	0.22	0.01	0.02	0.70	-0.04	0.38
HEALTHGOOD	-0.14	0.05	0.15	0.05	0.02	0.59	0.01	0.82
HEALTHVGOOD	-0.06	0.37	0.13	0.09	0.04	0.30	-0.03	0.50
INC50KUP	-0.02	0.82	0.05	0.59	-0.07	0.14	0.02	0.65
INC3050K	-0.07	0.31	0.09	0.22	-0.01	0.89	-0.01	0.79
INC2030K	-0.06	0.40	0.12	0.12	0.01	0.80	-0.05	0.26
INC1020K	0.05	0.49	0.01	0.88	0.02	0.60	-0.06	0.13
MIDWEST	-0.05	0.45	-0.05	0.50	0.02	0.62	0.01	0.79
SOUTH	0.18	0.00	0.02	0.79	0.16	0.00	-0.01	0.71
WEST	0.00	1.00	-0.04	0.63	0.04	0.34	0.00	0.97
_CONS	-4.89	0.00	0.68	0.49	-4.31	0.08	1.73	0.44
N	906		906		2618		2618	
R2	0.13		0.08		0.02		0.02	
ADJ R2	0.10		0.05		0.01		0.01	

Note:

1. Weighted average market drug qualities are calculated using scrip shares as the weights.
2. Weighted average market copayments are calculated using scrip shares as the weights.

Appendix 1a: Quality Indicators of NSAIDs

Variable Names	Description	Mean	Std Dev
PNRF	Effective Pain Relief (mean Rating)	3.71	0.13
CHRPNRF	Effective Relief of Chronic Pain	3.68	0.14
MNTEFF	Maintains Effectiveness After Extended Use	3.73	0.14
ANTIINFL	Effective Anti-Inflammatory Agent	4.01	0.11
IDLCHRO	Ideal Chronic Agent	3.66	0.22
IMPMOB	Improve Mobility and Range of Motion	3.72	0.13
PRVTR	Effective in Previous NSAID Treatment Failures	3.49	0.24
LONGDUR	Long Duration of Action	3.94	0.22
RAPONSET	Rapid Onset of Analgesic Action	3.32	0.21
IDLACUTE	Ideal Acute Agent	2.94	0.21
EXTUSE	Safer for Extended Use	3.64	0.29
GIBLD	Low Potential to Cause Ulcers/GI Bleeding	3.72	0.61
ELDER	Safe For Use in The Elderly (65+)	3.69	0.38
RENAL	Low Potential to Affect Renal Function	3.22	0.28
GIUPSET	Low Potential to Cause GI Upset (Nausea, Dyspepsia, etc.)	3.64	0.55
HEPATIC	Low Potential to Affect Hepatic Function	3.40	0.20
DUGINTER	Minimal Drug Interactions	3.43	0.20
BLDTIME	Minimal Effect on Platelet Aggregation/Bleeding Time	3.32	0.49

Appendix 1b: Quality Indicators of Antidepressants

Variable	Description	Mean	Std. Dev.
QLTYLF	Improve Patient's Quality of Life	4.08	0.11
MLDMOD	Effective for Mild to Moderate Depression	4.14	0.11
ENERGY	Increased Energy Level/Activation	3.67	0.24
TOLERATE	Well-Tolerated by Patients	3.75	0.18
INTERAC	Few Interaction with Other Drugs	3.68	0.18
SEXUAL	Low Incidence of Sexual Dysfunction	2.96	0.48
CHGWEIGHT	No Weight Gain/Change	3.28	0.28
SEDATION	Low Incidence of Daytime Sedation	3.68	0.34
AGITATION	Minimal Agitation	3.51	0.26
RAPID	Rapid Onset of Action	3.01	0.12

Chapter Three
Racial and Ethnic Disparities in Antidepressant Drug Use

Abstract

Background

Little is known about racial and ethnic disparities in health care utilization, expenditures and drug choice in the antidepressant market.

Aims

This study investigates factors associated with the racial and ethnic disparities in antidepressant drug use. We seek to determine the extent to which disparities reflect differences in observable population characteristics versus heterogeneity across racial and ethnic groups. Among the population characteristics, we are interested in identifying which factors are most important in accounting for racial and ethnic disparities in antidepressant drug use.

Methods

Using Medical Expenditure Panel Survey (MEPS) data from 1996-2003, we have an available sample of 10,416 Caucasian, 1,089 African American and 1,539 Hispanic antidepressant drug users aged 18 to 64 years. We estimate individual out-of-pocket payments, total prescription drug expenditures, drug utilization, the probability of

taking generic versus brand name antidepressants, and the share of drugs that are older, lower-quality types of antidepressants (e.g., TCAs and MAOIs) for these individuals during a calendar year. Blinder-Oaxaca decomposition techniques are employed to determine the extent to which disparities reflect differences in observable population characteristics versus unobserved heterogeneity across racial and ethnic groups.

Results

Caucasians have the highest antidepressant drug expenditures and utilization. African-Americans have the lowest drug expenditures and Hispanics have the lowest drug utilization. Relative to Caucasians and Hispanics, African-Americans are more likely to purchase generics and use a higher share of older, lower-quality drugs (e.g., TCAs and MAOIs). Differences in observable characteristics explain most of the racial/ethnic differences in these outcomes, with the exception of drug utilization. Differences in health insurance and education levels are particularly important factors in explaining disparities. In contrast, differences in drug utilization largely reflect unobserved heterogeneity across these population groups.

Conclusions

Substantive racial and ethnic disparities exist in all dimensions of antidepressant drug use examined. Observable population characteristics account for most of the differences in the expenditures, with health insurance and education key factors driving differences in spending. Observable characteristics are also important in

explaining racial and ethnic disparities in the probability of purchasing generics and in the quality of antidepressant drugs used. Differences in total utilization are not well-explained by observable characteristics, and may reflect unobserved heterogeneity such as unobserved physician-patient relationships, mistrust, and cultural factors.

Implications for Policy

Reducing differences in observable characteristics such as health insurance and education will mitigate racial and ethnic disparities in expenditures on antidepressant drug use and in the types of antidepressant used (e.g., generics vs. brands; higher quality vs. lower quality). But these factors will have less influence in reducing racial and ethnic disparities in overall antidepressant drug utilization. To limit differences in overall antidepressant drug use, policymakers must take into account cultural factors and other sources of heterogeneity.

3.1 INTRODUCTION

The antidepressant market is one of the largest therapeutic markets in the world. In 2007, antidepressant drugs ranked as the leading therapy class by dispensed prescription volume (IMS Health Report 2008). Sales of antidepressants are quite substantial and are likely to remain so. Global sales of antidepressants exceed $15 billion and the United States accounts for 71% of it (Research & Markets 2005). The prevalence of depression by race/ethnicity remains inconclusive. Some studies indicate that African-Americans have higher rates of major depressive disorder (Somervell et al, 1989, Neighbor et al, 1983). Other more recent studies reach the opposite conclusion (Blazer et al. 1994, Kessler 2003, Riolo et al. 2005).

Little is known regarding racial and ethnic disparities in utilization, spending, and types of drugs purchased in the antidepressant drug market. Identifying the extent and causes of such disparities is important because depression is a common and chronic disease, with patients frequently suffering recurrences or relapses (Thase 1990). Thus, patients who suffer from depression typically engage in ongoing use of antidepressant drugs. Gaskin et al. (2006) and Wang (2006) find evidence suggesting that unobserved heterogeneity may play an important role in explaining the disparity in drug utilization between different racial/ethnic groups. Melfi et al. (2000) find that a significant disparity exists between Caucasians and minorities in antidepressant drug utilization even after adjusting for other individual characteristics. They note that differences in access and drug compliance may be important sources of unobserved heterogeneity. Yet, there is no established literature identifying factors that explain

these disparities or quantify the effects of these factors on treatment patterns. We seek to understand whether and to what extent differences in observed characteristics such as income, education, health insurance, and unobservable heterogeneity account for racial and ethnic disparities in antidepressant drug use.

To help answer these questions, we use the Blinder-Oaxaca decomposition technique (Blinder 1973; Oaxaca 1973). This method has received only limited application in health services research generally, and in studying racial and ethnic disparities in health services use in particular. It is, however, quite useful in that it can not only distinguish how much observed versus. unobserved characteristics affect disparities, but can also determine the importance of individual factors in contributing to disparities. Such information should prove quite valuable from a policy perspective. Particularly, in this paper, we seek to determine the extent to which disparities reflect differences in observable population characteristics versus heterogeneity across racial and ethnic groups in antidepressant drug use, employing the Blinder-Oaxaca decomposition technique.

Using the Medical Expenditure Panel Survey (MEPS) data from 1996-2003, we estimate individual out-of-pocket payments, total prescription drug expenditures, drug utilization, the probability of taking generic versus brand name antidepressants, and the share of drugs that are older, lower quality types of antidepressants (e.g., TCAs and MAOIs) for Caucasian, African American, and Hispanic individuals. We find that substantive racial and ethnic disparities exist in all dimensions of antidepressant drug use examined. Observable population characteristics account for most of the

differences in drug expenditures, with health insurance and education key factors driving differences in spending. Observable characteristics are also important in explaining racial and ethnic disparities in the probability of purchasing generics and in the quality of antidepressant drugs used.

In contrast, differences in total utilization are not well-explained by observable characteristics, and may reflect unobserved heterogeneities. This finding suggests that, in order to mitigate differences in overall antidepressant drug use, policymakers must take into account these unobserved factors, such as mistrust, physician-patient interactions, and cultural factors. Thus, differences in observable characteristics (notably health insurance and education) explain racial and ethnic disparities in expenditures and patterns of use (e.g., brand vs. generic), but not disparities in total utilization.

To develop policies to reduce racial and ethnic disparities, it is important to know the relative importance of observed and unobserved parts and identify individual factors that are associated with the differences. Smedley et al (2003) reported that inconsistent treatment can increase overall health care expenditures. This topic is particularly timely now, as the proportion of minorities in the United States is growing substantially (US Bureau of the Census 2004). Understanding the extent and causes of these disparities can lead to more consistent, appropriate and effective policies aimed at their reduction.

3.2 BACKGROUND AND LITERATURE REVIEW

Expenditures and Utilization. Evidence (Drug Benefits Trends 2005) indicates that antidepressants were associated with the top 5 costliest drugs per member per year (PMPY) in 2002, averaging $50.46. Caucasians usually have higher drug expenditures and utilization than minorities (Gaskin et al. 2006, Blazer et al. 2000). Policymakers often encourage people to use generic drugs to control these costs. Understanding those factors affecting the gaps in drug utilization and expenditure patterns between Caucasians and minorities will inform policies to reduce these disparities.

Previous research on racial and ethnic disparities in pharmaceutical expenditures and use is quite limited, however. Gaskin et al. (2006) compare prescription drug expenditures among Caucasian, African-American and Hispanic Medicare beneficiaries. They find that total spending for whites was 8.9% and 5.4% more than for African-American and Hispanics, respectively, and that total out-of-pocket spending for whites was 28.8% and 10.7% more than for African-American and Hispanics. However, they found little difference in the number of prescriptions filled. Gaskin et al. (2006) is one of the few drug utilization studies to employ decomposition techniques to determine the importance of observed and unobserved factors in explaining racial and ethnic disparities in use. They find that population characteristics (observed factors) can explain most of the disparities in out-of-pocket payment for racial and ethnic disparities, and part of the total spending for ethnic disparities, but *unobserved* factors explained most of the differences in utilization.

Specifically, they find that, due to population characteristics only, whites would be expected to have *lower* utilization than minorities; however, race and ethnicity more than offset this effect, such that whites use 0.9 more prescriptions per year than blacks and 0.4 more than Hispanics. However, they do not report the roles of individual factors such as education or family income in accounting for racial and ethnic variations in drug use. Moreover, they examine overall measures of drug utilization and expenditure, not expenditures within a given drug product class.

White-means (2000) investigates racial differences in prescribed drug utilization among disabled elderly persons, finding very large differences due to race. Using the Oaxaca decomposition technique, the author finds very large differences due to race in the utilization of overall physician services and prescription medications.

Wang et al. (2006) examine racial and ethnic disparities in the utilization of new brand name prescription drugs (i.e. drugs that had been in the market for no more than 5 years), finding that Caucasians use 22-33% more new drugs than African-Americans, and 5-16% more than Hispanics. Again, they do not look at individual drug categories separately. Moreover, their results can not be generalized to generic drugs.

Blazer et al. (2000) find that whites used 2.3% more antidepressants in 1986 and the difference increased to 5.0% in 1996. Some other drug-specific studies, such as drugs for treating HIV and hypertension, also find that whites use more drug prescriptions than minorities (Hanlon et al. 1992, Smith and Kirking 1999, Chen and Chang 2002, Moore et al. 1994). These studies only looked at utilization patterns,

however, and did not employ decomposition methods to identify factors responsible for the observed disparities.

Most previous studies of racial and ethnic disparities in drug use focus on the utilization of particular drug groups without employing decomposition techniques to help isolate the determinants of racial and ethnic disparities. While White-means (2000) and Gaskin (2006) did employ decomposition methods, their analyses combine many different drugs across drug product classes. As a result, it is unclear whether their findings pertain to antidepressant drugs as a class. Our study will focus on the antidepressant market, and use decomposition techniques to ascertain the effects of individual factors on observed differences.

Patterns of Use. There is even less research on racial and ethnic disparities in patterns of drug use, such as the choice of generic versus brand name drugs. Gaither (2001) notes that consumers' attitudes toward generic drugs may differ by race and ethnicity. More specifically, Gaither suggests that minorities may have different access to the advertisements for brand-name drugs, and they may be more likely to feel negative about generics than their white counterparts.

In addition to the generic versus brand choice, which largely reflects differences in drug cost, it would be interesting to study racial and ethnic disparities in the quality of drugs used. In the context of antidepressant drugs, quality differences may be captured by examining differences in the use rate of older drugs such as tricyclics (TCAs) and monoamine oxidase inhibitors (MAOIs), which have been available in the U.S. for decades versus newer selective serotonin reuptake inhibitors (SSRIs) and

related new antidepressants.

While TCAs and MAOIs are effective in the treatment of depression, they have more serious side effects profiles and in the case of TCAs may be lethal in overdose. MAOIs may also cause serious problems due to lethal dietary and drug interactions. The SSRIs began to appear in the late 1980s and 1990s. They have similar effectiveness to TCAs and MAOIs, but with better-tolerated side effects. Most recently, additional antidepressants have become available, including non-selective serotonin reuptake inhibitors (NSRIs) and selective norepinephrine reuptake inhibitors. Smedley et al (2003) reported that "both racial and ethnic minorities tend to receive health care of lower quality and quantity than majority populations." Is this true in the antidepressant market? We will investigate whether Caucasians have a greater tendency to use the newer, higher quality antidepressants.

3.3 DATA AND METHODS

3.3.1 DATA

Our analysis employs data from the 1996-2003 Medical Expenditure Panel Survey (MEPS) conducted by the Agency for Healthcare Research and Quality (AHRQ). The MEPS database consists of a number of files, and we use three of them. The Consolidated File is a person-year level database, which provides detailed consumer information on health care utilization and expenditures as well as patients' demographics, socioeconomic characteristics, health, and health insurance status. The Prescribed Medicines File is an event-level file that includes information on the

utilization and payments for each drug used by survey respondents.[34] The Prescribed Medicines File also indicates whether the drug in question was brand or generic from 2002 onward. A third file we used from MEPS -- the Multum Lexicon file -- determined brand/generic status for the drugs before 2002. We converted the Prescribed Medicines File to the person-drug level (i.e. an individual who purchased two kinds of antidepressants are considered as two observations). Then, we merged it with the Consolidated File for this study. We repeat this merge every year and pool all the observations.

We compare racial disparities between Caucasian non-Hispanics (Caucasians) and African-American non-Hispanics (African-Americans), and the ethnic disparities between Caucasian non-Hispanics and Hispanics (Hispanics). We include all subjects aged 18 to 64 who had used any antidepressant drug during a calendar year. This left us with 10,416 Caucasian non-Hispanics, 1,089 African-American non-Hispanics and 1,539 Hispanics. Because the MEPS data sets provide very detailed information about drug utilization, expenditure and drug name for each prescription, we are able to analyze the racial and ethnic differential in the following five outcomes: out-of-pocket payments, total drug expenditures, drug utilization, the probability of taking generics versus brand names drugs, and the share of TCAs and MAOIs among all the

[34] Household respondents provided information on the names of all outpatient medications used by each household member and the names and locations of the pharmacies where medications were obtained. They were also asked for permission to request records from these pharmacies. Pharmacy providers were asked to provide information to enable MEPS to assign a national drug code, which identifies manufacturers, ingredients, strength, package size, quantity dispersed, total charge, and sources of payments. The AHRQ performed detailed matching, imputation, consistency checks, and sensitivity checks.

antidepressants taken.

3.3.2 METHODS

Racial and ethnic differences may reflect two broad sources: (1) differences from the observed population characteristics, such as insurance coverage, education, and family income; and (2) differences from unobserved factors, such as culture, mistrust, attitudes towards medicines, and physician-patient interactions. To develop policies to reduce racial and ethnic disparities, it is important to know the relative importance of these two components and identify individual factors that are associated with the differences. We address four related questions for each of these five outcomes.

1. *What is the magnitude of racial/ethnic differences?*
2. *What portion of these racial/ethnic differences reflects differences in levels of observed population characteristics?*
3. *What portion of these racial/ethnic differences reflects unobserved race/ethnicity effect?*
4. *How important are specific factors such as health insurance and education in accounting for explained differences?*

Conceptual framework. According to the behavioral model developed by Anderson (1973, 1995), utilization and expenditures on prescription drugs are determined by predisposing, enabling and need factors. We include such factors in our empirical models. Predisposing factors include individual characteristics such as age,

gender, marital status and education.

Enabling factors include health insurance coverage, family income, whether the subject has a regular source of care, MSA status (urban or rural) and census region dummies. Need factors include self-perceived mental health status, dummy variables measuring whether the patient has ADL (activities of daily living) limitations or IADL (instrumental activities of daily living) limitations. Since we pool data across years, time dummies are included to control for year-specific effects.

Our dependent variables include antidepressant utilization, individual out-of pocket-payment and total expenditures for antidepressant drugs [35]. We also investigate differences between Caucasians and African- Americans and Caucasians and Hispanics, respectively, in the probability of taking any generic antidepressant drugs, and the share of tricyclics (TCAs) and monoamine oxidase inhibitors (MAOIs) among all the antidepressants the individual took per year.

Specifically, we separate the antidepressants into 3 therapeutic classes: the selective serotonin reuptake inhibitors (SSRIs), such as PROZAC, ZOLOFT, and PAXIL; the tricyclics (TCAs) and monoamine oxidase inhibitors (MAOIs), such as AMITRIPTYLINE, NORTRIPTYLINE. We combine the rest of the antidepressants as the "other antidepressant" group, such as EFFEXOR, REMERON. Then we define share of TCAs and MAOIs as the ratio of utilization of TCAS or MAOIs to the

[35] Approximately 9% of the total observations for out-of-pocket payments have zero payment. We add 1 to out of pocket payments and then take the logarithm.

utilization of all antidepressants.

Decomposition technique. The technique to decompose the racial and ethnic disparities in various outcomes was first developed by Oaxaca (1973) and Blinder (1973). This method can decompose the disparities in average outcomes between racial and ethnic groups and quantify the role of individual factors in contributing to these differences.

To implement this procedure for continuous outcomes such as out-of-pocket payments, we first estimated OLS regression models for Caucasians using the independent variables specified in the previous section, with individual out-of-pocket payment as the dependent variable. Then we used the estimated coefficients and the mean values of all the independent variables to calculate the predicted out-of-pocket payments for each patient (equation (1)). We performed the same calculations for African-Americans (equation (2)).[36] Since some individuals might appear more than once during a year because they purchased different kinds of antidepressants, we corrected the standard errors for the regression models (Greene 2002). Thus we estimate:

$$\ln(\overline{PAY}_W) = \overline{X}'_W \hat{\beta}_W \qquad (1)$$

$$\ln(\overline{PAY}_B) = \overline{X}'_B \hat{\beta}_B \qquad (2)$$

[36] We transformed our prescription expenditure variables by taking the logarithms, because of its skewed distribution. Since we use the logarithm form of the payment, we should interpret the difference in payment as the percentage.

where the *X*s include all the individual characteristics described in the conceptual model (the predisposing, need and enabling factors), and $\hat{\beta}$ s are the coefficients associated with the *X*s.

Subtracting equation (2) from equation (1), we obtain:

$$\ln(\overline{PAY}_W) - \ln(\overline{PAY}_B) = (\overline{X}_W' - \overline{X}_B')\hat{\beta}_W + \overline{X}_B'(\hat{\beta}_W - \hat{\beta}_B) \qquad (3)$$

From equation (3), we can see that the Blinder-Oaxaca decomposition allows us to decompose the differences in individual out-of-pocket payments into 2 portions: the portion due to all the observed independent variables across racial groups (the first term on the right-hand side); and the portion due to differences in the coefficients (immeasurable or unobserved factors) across the racial groups.

As shown in equation (3), the individual characteristics portion of the Blinder-Oaxaca decomposition is given b y $(\overline{X}_W' - \overline{X}_B')\hat{\beta}_W$. As Caucasians are the reference groups in these decompositions, any positive number is associated with higher spending for Caucasians. A number close to zero indicates that there are similar levels for Caucasians and African Americans. The same approach is used for the other continuous outcomes and is also applied to Caucasians and Hispanics. We do not further analyze how much each individual factor can contribute to this "unexplained" portion of differences because of the difficulty in interpreting those results (Jones 1983, Oaxaca and Ransom 1997). [37]

[37] Jones (1983) notes that it is arbitrary to further interpret the second term on the left-hand-side of equation (3) as the differences in coefficients and the differences in the intercept terms. In particular, he argues that the intercept and dummy variable coefficients differ according to the different reference group chosen for the dummy variables. The intercept will also differ

The non-linear Blinder-Oaxaca decompositions are applied to the regressions which estimate the probability of purchasing generics versus brands and the number of prescriptions purchases, respectively.. For the model with the probability of taking generics among different racial and ethnic groups, we can not apply Blinder-Oaxaca decomposition technique directly because of the model's nonlinearity. Following Fairlie (2005) & Bartus (2006), the decomposition for a nonlinear equation, $Y = F(X\hat{\beta})$, may be written as:

$$\bar{Y}^W - \bar{Y}^B = [\sum_{i=1}^{N^W} \frac{F(X_i^w \hat{\beta}^W)}{N^W} - \sum_{i=1}^{N^B} \frac{F(X_i^B \hat{\beta}^W)}{N^B}] + [\sum_{i=1}^{N^B} \frac{F(X_i^B \hat{\beta}^W)}{N^B} - \sum_{i=1}^{N^B} \frac{F(XB_i^w \hat{\beta}^B)}{N^B}] \quad (4)$$

Similar to the linear Blinder-Oaxaca decomposition, the first term on the right-hand-side of equation (4) measures the portion of the difference due to observable population characteristics.

The number of prescriptions in our data set is discrete and right-skewed. The distribution of this variable thus violates the assumption of Poisson regression that the conditional mean equals the conditional variance. Hence, we employ the negative binomial model to take into account this overdispersion issue (Bartus 2006). [38]

3.4 RESULTS

3.4.1 DESCRIPTIVE ANALYSIS

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by the scale of the continuous variables. Oaxaca and Ransom (1997) further argued that the interpretation of the coefficient and intercept varies when more than one dummy variable is included in the model.

[38] We test the overdispersion using the likelihood ratio chi-square test. The result shows that the overdispersion parameter is significantly different from zero, implying overdispersion.

Summary statistics for the study characteristics are given in Table 1. Caucasians have the highest out-of-pocket payment and drug expenditures. This may reflect a greater tendency of Caucasians to purchase more expensive, brand-name drugs as well as SSRIs and other relatively new antidepressants. Caucasians have the highest drug utilization. We are unable to infer from the data whether Caucasians are over-consuming antidepressant drugs. Some researchers have suggested that minorities under utilize these drugs (Kales 2000, Blazer 2000).

Caucasians have the highest education and income levels, the highest enrollment rates in private health insurance and the lowest in public health insurance. Since we examine subjects aged 18 to 64, the vast majority of public health insurance in our study comes from Medicaid.

(INSERT TABLE 1)

3.4.2 DECOMPOSITION RESULTS

Caucasians and Hispanics. Table 2 shows the results of the decomposition estimates comparing Caucasians with Hispanics. The top panel lists the predicted mean value for each dependent variable and the total differences for each of the five outcome measures. We also separate the total differences into the differences due to population characteristics (i.e. the differences due to differences in levels of the variables) and differences from the unobserved heterogeneity. We further break down each characteristic's contribution to the differences and list the results at the bottom panel of the table.

Out-of-pocket payment is $12.14, for Caucasians, compared to $9.69 for Hispanics. Caucasians pay 17.6% more than Hispanics due to differences in the observed characteristics, and 5% more due to the differences in the unobserved characteristics. In other words, approximately 78% (17.6/22.6) of the total differences in out-of-pocket payment are explained by the observed population characteristics. Among these observed factors, insurance status is the most important reason to explain the differences in out-of-pocket payments betweens Caucasians and Hispanics. More specifically, public health insurance is the main factor for differences in out-of-pocket payment. The results also reveal that subjects with public health insurance tend to pay less out-of-pocket. Larger proportions of Hispanics are enrolled in public health insurance than Caucasians, and this difference increases the payment gap. In other words, if more Caucasians had public insurance, the-out-of pocket payment gap would decline.

(INSERT TABLE 2)

Regarding total expenditures, Caucasians pay $51.39 on average, which is 11.8% more than Hispanics. Differences in population characteristics result in 7.1% more expenditures and unobserved heterogeneity accounts for the remaining 4.7, about 40% (4.7/11.8) of the total difference. Differences in education between Caucasians and Hispanics have the strongest effect on total expenditure disparities, followed by differences in health status. Thus, if Hispanics had the same level of education and health status, the total expenditure disparities would drop by 37.3%.

With respect to differences in the number of prescriptions filled, we estimate that

Caucasians purchase 0.9 more prescriptions per year than Hispanics. The differences in population characteristics do not explain these differences in drug utilization, however. Indeed, based on observable characteristics alone, Caucasians would be predicted to fill slightly *fewer* prescriptions than Hispanics. It is the unobserved heterogeneity that drives the actual difference in drug utilization, leading Caucasians to purchase 0.9 more prescriptions. Therefore, most of the disparity in utilization is due to the unobserved heterogeneity between Caucasians and Hispanics.

Caucasians are 5% less likely to purchase generics compared to Hispanics. Observed differences in population characteristics explain approximately 80% (0.04/0.05) of the total difference. Health insurance status and family income are the most important specific factors affecting these differences, followed by education and employment status. Thus, if Hispanics had the same family income as Caucasians, differences in the probability of purchasing generics would decline by 8%. If Caucasians had the same enrollment level in private and public health insurance, the gap would decline by 28%.

Caucasians are substantially less likely to purchase older TCAs or MAOI antidepressants than are Hispanics. Population characteristics explain about 32% (0.02/0.09) of the difference. Caucasians' favourable status in education and private health insurance are the main individual factors associated with their tendency to purchase a greater share of SSRIs and other new antidepressant drugs.

Caucasians and African-Americans. Table 3 shows the results of the Blinder-Oaxaca decomposition for Caucasians and African-Americans. African-Americans

have the lowest out-of-pocket payment and total drug expenditure and the highest probability of purchasing generics and older antidepressant drugs (TCAs and MAOIs). Drug utilization of African-American is lower than Caucasians, though higher than Hispanics.

Out-of-pocket payment for African-Americans is $7.20, far lower than that of Caucasians ($12.14). Observed characteristics explain 60% (31.4/52.2) of the total difference, among which the difference in public health insurance is the major source for the disparity. Similar to the disparity between Caucasians and Hispanics, if Caucasians had the same level of public health insurance as African do, the out-of-pocket payment gap would disappear.

On average African-Americans spent $41.29 in total for each prescription, about $10 less than Caucasians, of which 18% (3.9/21.9) of the difference can be explained by observed characteristics. Caucasians' favorable status in private health insurance is the main reason for the disparity between Caucasians and African-Americans. Caucasians' better health status is also an important reason for the disparity here.

(INSERT TABLE 3)

Turning to utilization of prescription drugs, the effects of differences due to population characteristics are offset by unobserved racial differences. That is, Caucasians purchase 0.43 fewer prescriptions due to differences in population characteristics. However, they purchase 0.93 more due to the impact of race differences. Collectively, these two effects lead to a total difference of 0.5

prescriptions per year. Similar to the utilization disparity between Caucasians and Hispanics, unobserved heterogeneity is the main source driving differences between Caucasian and African-Americans in terms of drug utilization.

African-Americans are 10% more likely to purchase generics compared to Caucasians, and 40% (0.04/0.10) of this difference is due to the observed population characteristics. The difference in health insurance is the most important specific reason for the disparity. African-Americans also have a higher (10%) share of TCA and MAOIs compared to Caucasians. Employment status and health insurance status are the most important reasons to explain these differences in share of TCA and MAOIs.

Summary. For all of the five decomposition results, differences in population characteristics explain a larger share of Caucasians-Hispanic disparities than is the case for Caucasian-African-American disparities. The differences in observable characteristics explain racial and ethnic disparities in expenditures and patterns of use (e.g., brand vs. generic), but not disparities in total utilization. The main reasons for racial and ethnic disparities for these five outcomes are summarized in Table (4).

(INSERT TABLE 4)

Out-of-pocket expenditures. As Table 4 indicates, the most important reason for differences in out-of-pocket payment is the difference in public and private health insurance coverage. The gaps will decrease substantially if Caucasians would have the same enrollment rate in public health insurance as African-Americans/Hispanics, or

African Americans/Hispanics had the same private health insurance as Caucasians.

Total drug expenditures. Differences in private health insurance coverage and education are the main reasons for differences in total drug expenditures between either Caucasians and African-Americans or Caucasians and Hispanics respectively. This suggests that, in order to reduce differences in total expenditures, policy makers should not only focus on the lower health insurance coverage but also the educational attainment of minorities.

Utilization. Unobserved heterogeneity, not observable characteristics, explains the higher drug utilization of Caucasians. The unobserved patients' cultural background, mistrust, and physician-patient relationships are all possible explanations for these disparities.

Patterns of use. Health insurance status, and are the most important factors accounting for differences in the probability of taking generics and the share of TCA and MAOIs between Caucasians and African-Americans and Caucasians and Hispanics, respectively.

3.5 DISCUSSION

This study examines racial and ethnic disparities in out-of-pocket payments, total expenditures, utilization, the probability of taking generic drugs and the share of the TCAs and MAOIs for antidepressant drug users. Differences in population characteristics (predisposing, enabling and need factors) can explain major differences in drug expenditures. In terms of specific factors, we find that education, family

income and health insurance are major reasons for these differences. Education is one of the predisposing characteristics in determining individual drug expenditure. We find that education is more important in explaining differences between Caucasians and Hispanics than between Caucasians and African-Americans. In contrast, other predisposing factors, such as age and gender, do not explain these differences.

Health insurance is an enabling factor as explained in Anderson's (1973) model. We find health insurance to be particularly important in accounting for differences in out-of-pocket payment and patterns of drug use (e.g., brands vs. generics and newer vs. older types of antidepressants).

Differences in population characteristics, however, cannot explain disparities in total antidepressant drug utilization. Our results show that if there is no race/ethnicity (e.g. unobserved heterogeneity) effect, Caucasians will purchase fewer prescribed drugs. However, the influence of the race/ethnicity results in greater utilization for Caucasians. Therefore, unobserved heterogeneity is the main source driving differences between Caucasian and minorities in antidepressant utilization. This result is consistent with the literature (Gaskin et al. (2006), Hanlon et al. (1992), Smith and Kirking 1999, Chen and Chang 2002).

Race-specific differences in unobserved factors such as mistrust, patients' skepticism about medications, drug compliance practices, physician prescribing behavior, and the patient-physician relationship may be important components of racial and ethnic disparities in drug use. This may be particularly true for the treatment of depression. The literature attests that depression is a chronic illness, and

patients frequently suffer recurrences or relapses (Thase 1990). Maintaining a healthy relationship with one's physician and good drug compliance practices are very important. To decrease disparities in the antidepressant utilization between Caucasians and minorities, policy makers need to focus on these behavioral issues beyond observed population characteristics.

Limitations. There are several limitations of this study. First, since we do not have detailed ICD9 codes, we are unable to distinguish a group of people who have been diagnosed with major depression but did not take antidepressants. In many cases, antidepressant drugs are used off-label (Medical Studies/Trials 2006). To identify a viable control group of non-users who might be candidates for antidepressant drugs, we would need to identify a cohort of non-users who might benefit from antidepressant drug use as well. But this is not possible given the information available in the MEPS database. Thus, in this study we only include people who are already users of antidepressants. These subjects might differ from current non-users of antidepressants who could conceivably benefit from treatment. Second, we do not have linked information between physicians and their patients. Therefore, we are unable to purge the unobserved factors that might be related to physician characteristics and physician behavior toward their patients. For example, physicians might have different prescribing patterns for patients according to race and ethnicity[39] . Third, while we have attempted to control for observed characteristics that capture the predisposing, enabling, and need features of Anderson's (1973) model,

[39] We thank an anonymous reviewer for calling this point to our attention.

additional factors or greater detail among the variables we can measure might enhance the ability to account for racial differences based on these three features of Anderson's model.

Policy Implications. We find that observed factors explain important components of racial and ethnic disparities in antidepressant drug spending and in the types of antidepressant drugs used. Polices aimed at reducing disparities in education, income, unemployment, and health insurance should play an important role in reducing racial and ethnic disparities in antidepressant drug spending and in the types of drugs used. In contrast, our findings suggest that these policy changes may have relatively modest effects on the overall utilization of antidepressant drugs, arguably the most critical outcome from the standpoint of patient welfare. Eliminating disparities in overall utilization may require addressing some key factors such as racial and ethnic differences in communication with health care providers, beliefs about the efficacy of drug use, and other cultural factors.

Table 3.1: Summary Statistics (Means, standard deviation in the parenthesis).

VARIABLES (MEAN)	Description	Caucasian N=10416	African-American N=1089	Hispanics N=1539
LN(OUT-OF-POCKET)	Ln of subject's out-of-pocket payment	2.5 (1.35)	1.98 (1.70)	2.27 (1.61)
LN(TOTAL EXPENDITURE)	Ln of subject's total expenditure for each prescription.	3.94 (0.92)	3.72 (1.05)	3.82 (1.01)
NUMBER OF PRESCRIPTIONS	Number of prescriptions subject purchased during a survey year	4.81 (3.92)	4.31 (3.68)	3.93 (3.79)
PROB(GENERIC)	Probability of subject purchase generic antidepressant	0.24 (0.43)	0.33 (0.47)	0.29 (0.45)
SHARE OF TCA AND MAIOS	Ratio of number of TCA/MAIOs to the total antidepressants subject purchased	0.15 (0.33)	0.25 (0.41)	0.23 (0.40)
AGE	subject's age from 18 to 64	44.31 (11.11)	45.46 (10.58)	43.97 (11.23)
FEMALE	DV=1 if subject is female else=0	0.72 (0.45)	0.76 (0.43)	0.79 (0.40)
EDUC	Years of schooling	12.96 (2.54)	11.88 (2.49)	10.62 (3.87
MARRIED	DM=1 if subject is married else=0	0.50 (0.50)	0.23 (0.42)	0.46 (0.50)
FAMINC	Subject's annual family income	52625.09 (42848.06)	28505.8 (28392.07)	36178.74 (34678.29)
UNEMPL	DM=1 if subject is unemployed	0.30 (0.46)	0.55 (0.50)	0.47 (0.50)
PRVINS	DV=1 if subject has private health insurance else=0	0.74 (0.44)	0.40 (0.49)	0.47 (0.50)
PUBINS	DV=1 if subject has public health insurance else=0	0.19 (0.39)	0.52 (0.50)	0.38 (0.48)
UNINSURED	DV=1 if subject is uninsured else=0	0.07 (0.26)	0.08 (0.28)	0.16 (0.36)
HAVEUSC	DV=1 if subject has usual source care else=0	0.93 (0.26)	0.94 (0.23)	0.90 (0.29)
MHEALTHPOOR	DV=1 if subject's mental health status is poor else=0	0.08 (0.26)	0.13 (0.33)	0.09 (0.28)
MHEALTHFAIR	DV=1 if subject's mental health status is fair else=0	0.20 (0.40)	0.30 (0.46)	0.25 (0.43)
MHEALTHGOOD	DV=1 if subject's mental health status is good else=0	0.34 (0.47)	0.28 (0.45)	0.32 (0.47)
MHEALTHVGOOD	DV=1 if subject's mental health status is very good else=0	0.24 (0.43)	0.14 (0.35)	0.18 (0.38)

MHEALTHEXC	DV=1 if subject's mental health status is excellent else=0	0.15 (0.36)	0.15 (0.36)	0.16 (0.37)
HEALTHPOOR	DV=1 if subject's overall health status is poor else=0	0.14 (0.35)	0.23 (0.42)	0.19 (0.39)
HEALTHFAIR	DV=1 if subject's overall health status is fair else=0	0.19 (0.39)	0.30 (0.46)	0.28 (0.45)
HEALTHGOOD	DV=1 if subject's overall health status is good else=0	0.30 (0.46)	0.27 (0.44)	0.28 (0.46)
HEALTHVGOOD	DV=1 if subject's overall health status is very good else=0	0.25 (0.44)	0.15 (0.36)	0.15 (0.36)
HEALTHEXC	DV=1 if subject's overall health status is excellent else=0	0.11 (0.31)	0.05 (0.22)	0.075 (0.26)
ADL	DV=1 if subject has ADL (Activities of Daily Living) limitations else=0.	0.04 (0.19)	0.07 (0.26)	0.05 (0.23)
IADL	DV=1 if subject has IADL (Instrumental Activities of Daily Living) limitations else=0.	0.08 (0.28)	0.17 (0.38)	0.11 (0.31)
URBAN	DV=1 if subject lives in MSA else=0	0.73 (0.44)	0.81 (0.40)	0.89 (0.31)
MIDWEST	DV=1 if subject lives in Midwest Census Region else=0	0.26 (0.44)	0.21 (0.41)	0.08 (0.28)
SOUTH	DV=1 if subject lives in South Census Region else=0	0.38 (0.48)	0.53 (0.50)	0.34 (0.47)
WEST	DV=1 if subject lives in West Region else=0	0.20 (0.40)	0.12 (0.33)	0.36 (0.48)
NORTHEAST	DV=1 if subject lives in North East Census Region else=0	0.16 (0.37)	0.14 (0.35)	0.21 (0.41)
YR1996	DV=1 if year is 1996 else=0	0.07 (0.25)	0.07 (0.26)	0.07 (0.25)
YR1997	DV=1 if year is 1997 else=0	0.06 (0.23)	0.05 (0.23)	0.07 (0.25)
YR1998	DV=1 if year is 1998 else=0	0.10 (0.30)	0.08 (0.27)	0.12 (0.32)
YR1999	DV=1 if year is 1999 else = 0	0.10 (0.30)	0.07 (0.26)	0.10 (0.29)
YR2000	DV=1 if year is 2000 else=0	0.10 (0.31)	0.10 (0.31)	0.10 (0.31)
YR2001	DV=1 if year is 2001 else=0	0.18 (0.38)	0.17 (0.38)	0.15 (0.36)
YR2002	DV=1 if year is 2002 else=0	0.21 (0.41)	0.24 (0.42)	0.19 (0.40)
YR2003	DV=1 if year is 2003 else=0	0.19 (0.39)	0.22 (0.41)	0.20 (0.40)

Table 3.2: Decomposition Results for Caucasians and Hispanics

	OUT OF POCKET PAYMENT	TOTAL EXPENDITURE	NUMBER OF PRESCRIPTIONS	PROB GENERIC	SHARE OF TCA/MAO
CAUCASIAN	12.14	51.39	4.80	0.24	0.15
HISPANIC	9.69	45.65	3.92	0.29	0.23
TOTAL DIFFERENCES	22.60	11.80	0.89	-0.05	-0.09
DIFFERENCES DUE TO OBSERVED PART	17.60	7.10	-0.03	-0.04	-0.02
DIFFERENCES DUE TO UNOBSERVED HETEROGENIETY	5.00	4.70	0.92	-0.01	-0.06
AGE	0.00	-0.20	0.01	-0.001	0.001
FEMALE	0.10	-0.20	-0.02	0.000	0.000
EDUC	5.40	2.60	0.09	-0.003	-0.010
MARRIED	0.10	0.00	0.00	0.000	0.001
FAMINC	1.20	0.50	0.03	-0.004	-0.001
UNEMPL	1.10	0.00	-0.10	-0.003	-0.003
PRVINS	-28.90	0.90	0.06	-0.006	-0.008
PUBINS	35.80	0.30	-0.13	-0.008	0.001
HAVEUSC	-0.40	0.00	0.01	0.001	0.000
HEALTHFAIR	0.60	-0.10	0.00	0.000	0.002
HEALTHGOOD	0.00	0.10	0.00	-0.002	0.000
HEALTHVGOOD	0.50	2.00	0.01	-0.010	-0.011
HEALTHEXC	0.20	0.80	0.01	-0.004	-0.006
MHEALTHFAIR	0.00	0.00	0.02	0.001	-0.001
MHEALTHGOOD	0.00	-0.10	0.00	-0.001	0.000
MHEALTHVGOOD	0.30	-1.20	-0.06	0.007	0.011
MHEALTHEXC	0.00	0.30	0.01	0.001	0.000
ADL	0.10	0.00	0.00	0.000	0.000
IADL	0.00	0.10	-0.01	0.000	-0.001
LOCAL DUMMY	1.10	0.70	0.04	-0.010	0.000
YEAR DUMMY	0.10	0.50	0.00	0.002	0.000

Note: All the variables are defined in Table (1). For the insurance variables, uninsured people are the reference group in the OLS regressions. All the OLS regressions results are available upon request.

Table 3.3: Decomposition Results for Caucasians and African-Americans

	OUT OF POCKET PAYMENT	TOTAL EXPENDITURE	NUMBER OF PRESCRIPTIONS	PROB GENERIC	SHARE OF TCA/MAO
CAUCASIAN	12.14	51.39	4.80	0.24	0.15
AFRICAN-AMERICAN	7.20	41.29	4.31	0.33	0.25
TOTAL DIFFERENCES	52.20	21.90	0.50	-0.10	-0.10
DIFFERENCES DUE TO OBSERVED PART	31.40	3.90	-0.43	-0.04	-0.01
DIFFERENCES DUE TO UNOBSERVED HETEROGENEITY	20.80	18.00	0.93	-0.06	-0.09
AGE	0.10	0.50	-0.03	-0.006	-0.003
FEMALE	0.00	-0.10	-0.01	0.000	0.000
EDUC	2.50	1.20	0.04	-0.001	-0.004
MARRIED	0.80	0.20	-0.01	0.001	0.004
FAMINC	1.80	0.70	0.05	-0.006	-0.001
UNEMPL	1.70	0.00	-0.15	-0.005	-0.005
PRVINS	-35.70	1.10	0.07	-0.007	-0.009
PUBINS	62.20	0.60	-0.22	-0.014	0.001
HAVEUSC	0.30	0.00	-0.01	0.000	0.000
HEALTHFAIR	0.80	-0.10	0.00	0.000	0.002
HEALTHGOOD	0.00	0.30	0.00	-0.003	-0.001
HEALTHVGOOD	0.50	2.00	0.01	-0.012	-0.013
HEALTHEXC	0.40	1.30	0.02	-0.006	-0.010
MHEALTHFAIR	-0.10	0.10	0.03	0.001	-0.002
MHEALTHGOOD	0.10	-0.50	-0.02	0.001	0.003
MHEALTHVGOOD	0.40	-1.90	-0.09	0.011	0.014
MHEALTHEXC	0.00	0.00	0.00	0.002	0.002
ADL	0.30	-0.10	0.00	-0.001	0.000
IADL	0.00	0.30	-0.04	-0.001	-0.002
LOCAL DUMMY	-2.80	-0.50	-0.03	0.008	0.006
YEAR DUMMY	-1.80	1.20	-0.02	0.000	0.001

Note: All the variables are defined in Table (1). For the insurance variables, uninsured people are the reference group in the OLS regressions. All the OLS regressions results are available upon request.

Table 3.4: Summary of Main Factors to Increase the Gap in the Following Five Outcomes

	RACIAL DISPARITY (CAUCASIAN V.S. AFRICAN-AMERICAN)	ETHNIC DISPARITY (CAUCASIAN V.S. HISPANIC)
OUT-OF-POCKET	Public Health Insurance	Public Health Insurance
TOTAL EXPENDITURE	Private Health Insurance	Education
NUMBER OF PRESCRIPTIONS	Unobserved Factors	Unobserved Factors
PROB(GENERIC)	Public Health Insurance	Private/Public Health Insurance,
SHARE OF TCA AND MAIOS	Private Health insurance, Unemployment, Education	Education

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